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Published in:
Proc. of 2nd International Conference on Renewable Energies Offshore - RENEW 2016

Revenue optimization for the Ocean Grazer wave energy converter through storage utilization

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ABSTRACT: Increased penetration of renewable energy generation motivates a change of paradigm in the way power systems are structured and operated, as advocated by the smart grid concept. Accordingly, in this paper we investigate the lossless storage capabilities of the Ocean Grazer wave energy converter (WEC), which could facilitate the aforementioned paradigm shift. This specific WEC exhibits both adaptability with respect to the incoming waves and significant lossless storage capabilities. We propose a model predictive control (MPC) strategy based on a lumped dynamical model in order to mitigate power imbalances in the power grid and maximize the revenue of the WEC. Furthermore, we illustrate that the proposed strategy exploits the WEC energy storage capabilities and we show the economic benefits it brings. Lastly, the proposed strategy is compared with a heuristic approach and a setting without storage.

1 INTRODUCTION

The worldwide change towards increased usage of renewable energy sources due to fossil fuel depletion, global warming, and the recent sharp changes in the weather —among other reasons— call for a paradigm shift in power systems' structure and operation. The former has gained a lot of attention in recent years, for example, due to coral bleaching (Hoegh-Guldberg 1999), and the loss of reef islands in the Solomon Islands caused by sea level rise and coastal erosion (Albert, Leon, Grinham, Church, Gibbes, & Woodroffe 2016). The aforementioned shift —closely related to the smart grid concept— entails a different operation of power grids, the incorporation of more decentralized renewable energy generation, and the utilization of storage and flexible demand.

Ocean energy is one of the renewable energy sources that shows a lot of promise by harnessing the untapped power of ocean waves. Extraction of such energy can be realized through a device commonly known as a wave energy converter (WEC) (Drew, Plummer, & Sahinkaya 2009, Ringwood, Bacelli, & Fusco 2014). Recently, the Ocean Grazer platform has been proposed as a means to harvest the latent potential energy from the waves. The Ocean Grazer WEC (van Rooij, Meijer, Prins, & Vakis 2015, Vakis & Anagnostopoulos 2016) utilizes a novel power take-off (PTO) system that provides adaptability to a large range of waves with different periods and heights, as well as lossless storage by pumping water to an upper reservoir, which can then be released at a suitable time. The working principle is similar to storing potential energy in hydroelectric plants; see, for example, (Zhao & Davison 2009) for the profit optimization of a hydroelectric plant, and (Pritchard, Philpott, & Neame 2005, Steeger, Barroso, & Rebennack 2014) for market integration of hydraulic power plants.

In this paper, we propose a control strategy that aims to maximize the potential energy storage using predictions based on a net flow dynamical model. The former is a model predictive control (MPC) strategy, which has been successfully implemented in process control and provides a good framework for optimizing the operation of a system while respecting the system constraints. Recently, several MPC-based strategies for WECs have been proposed since energy capture can be maximized while handling constraints and mechanical limitations, and wave prediction can be incorporated; for example, in (Brekken 2011) a linear MPC and in (Richter, Magaña, Sawodny, & Brekken 2013) a non-linear MPC are proposed for a point-absorber WEC, respectively. The problem for point-absorbers has also been tackled from the perspective of dynamic programming as in (Li, Weiss, Mueller, Townley, & Belmont 2012), and optimal control as in (Abraham & Kerrigan 2013, Nielsen, Zhou, Kramer, Basu, & Zhang 2013).

More precisely, we explore the storage capabilities of the Ocean Grazer WEC by means of an optimization-based control strategy that aims to maximize the advantages of potential energy storage. Due to power fluctuations coming from other renewable sources, the storage capabilities of the WEC can be used to counter imbalances by releasing the stored water at a suitable time. The proposed control strategy is optimization-based (Bertsekas 1999, Boyd & Vandenberghe 2004) and relies on a lumped dynamical model, which characterizes the aggregated behavior of the WEC. Furthermore, the proposed strategy effectively increases the revenue of the WEC. As opposed to other strategies in the literature, the considered dynamics are based on the net flow of the WEC instead of being derived through the equations of motion; for details on the different types of WECs see (Ringwood, Bacelli, & Fusco 2014) and the references therein.

The remainder of the paper is organized as follows: in Section 2, the dynamic lumped model is presented, which is then used in Section 3 to design the revenue maximizing control strategy. Subsequently, simulation results are shown in Section 4, where the proposed strategy is compared against a heuristic decision model and a setting without storage. Lastly, concluding remarks are given in Section 5.

2 DYNAMIC MODELING

The dynamical model summarized in this section describes the change in internal fluid levels in the upper and lower reservoirs of the Ocean Grazer WEC, namely L_u and L_l, respectively. Furthermore, the upper and lower reservoirs have areas A_u and A_l, respectively. A sketch of the dynamic model is presented in Figure 1, where Q_p represents the pumping rate from the lower to the upper reservoir, and Q_v is the valve draining rate that allows for flow from the upper to the lower reservoir. Detailed information on the WEC is given in (Vakis & Anagnostopoulos 2016).

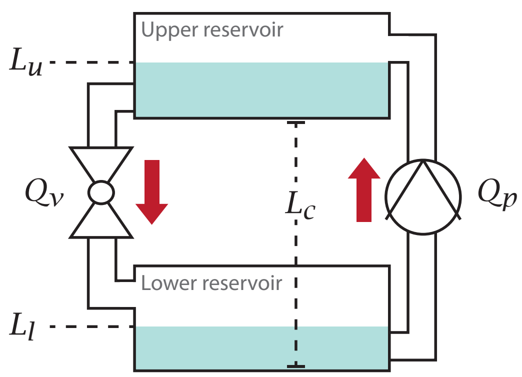

Figure 1: Lumped Dynamical Model of the Ocean Grazer.

We can characterize the behavior of each reservoir as a fluid capacitance using the macroscopic conservation law of mass (Asbjørnsen 1986). Hence, for the upper reservoir we have

$$\frac{\mathrm{d}V\rho_c}{\mathrm{d}t} = Q_p\rho_c - Q_v\rho_c, \tag{1}$$

where $V = A_u L_u$ is the conditioned fluid volume with density ρ_c within the reservoir. Under the assumption of V being perfectly mixed, such that the density ρ_c remains constant over the whole volume, we can simplify (1) as

$$\frac{\mathrm{d}L_u}{\mathrm{d}t} = \frac{1}{A_u}(Q_p - Q_v), \tag{2}$$

where the right-hand side represents the net flow of the WEC. Analogously, the change of fluid level in the lower reservoir yields

$$\frac{\mathrm{d}L_l}{\mathrm{d}t} = \frac{1}{A_l}(Q_v - Q_p). \tag{3}$$

Since the system representing the Ocean Grazer WEC is isolated from the sea environment, the levels in the upper and lower reservoir are related by

$$L_u + L_l = C, \tag{4}$$

with the constant C being the fluid capacity level of the WEC. Consequently, the hydraulic head of the WEC is given in terms of the reservoir levels and the constant height L_c, describing the length between the reservoirs, as

$$h = L_c + L_u - L_l, \tag{5}$$

which can be rewritten only in terms of L_u by using (4) as

$$h = L_c + 2L_u - C = 2L_u + \lambda, \tag{6}$$

and introducing the constant $\lambda := L_c - C$. Note that we only need either L_u or L_l to track the dynamics of the system. Thus, we let our state variable be $x := L_u$ and consider (2) to characterize the dynamics of the WEC lumped model in Subsection 2.3.

2.1 *Pumping Rate*

In order to obtain the pumping rate Q_p of the Ocean Grazer WEC, we take the extracted power from the incoming wave assuming linear wave theory (Falnes 2002, Falnes 2007), namely

$$P = \frac{\rho_{sw} g^2}{64\pi} w_f H_w^2 T_w, \tag{7}$$

where g is the gravity acceleration constant, ρ_{sw} is the sea water density, w_f is the wave front of the device, H_w is the wave height and T_w is the wave period. Thus, the pumping rate Q_p can be determined from the power gained by a fluid from a pump using the power expression in (7) and the hydraulic head in (6) as

$$Q_p = \eta \frac{P}{\rho_c g h} = \frac{\eta \rho_{sw} g w_f H_w^2 T_w}{64\pi\rho_c(2x+\lambda)}, \tag{8}$$

where $\eta = \eta_p + \eta_m$ is the combined pumping and mechanical efficiency.

2.2 *Draining Rate*

The draining rate expression we derive in this section describes the drainage of the upper reservoir by means of a valve that permits fluid flow through a turbine, which converts the stored potential energy into electrical energy. Accordingly, energy losses need to be considered since the conditioned fluid meets certain resistance while being transported to the lower reservoir; thus, we consider

$$K = K_f + K_t, \tag{9}$$

where K_f corresponds to the losses due to friction with the pipes walls and the valve, and K_t corresponds to the loss coefficient of the turbine, calculated as

$$K_t = \frac{2g\mu_h\eta_t}{v_f^2}, \tag{10}$$

where μ_h is the average hydraulic head of the WEC, η_t is the turbine efficiency and v_f is the average velocity of the flow through the turbine (Bansal 1986). Consequently, the draining rate Q_v can be written as

$$Q_v = A_v u\sqrt{\frac{2gh}{K+1}} = A_v u\sqrt{\frac{2g(2x+\lambda)}{K+1}}, \tag{11}$$

with A_v being the area of the valve, $u \in [0,1]$ being the opening degree of the valve —and the decision variable— and K being the losses described in (9).

2.3 *WEC lumped model*

Putting together the pumping rate Q_p in (8) and the draining rate Q_v in (11) into (2) results in the lumped model of the WEC, namely

$$\dot{x} = \frac{1}{A_u}\left(\frac{\eta\rho_{sw}gw_f z}{64\pi\rho_c(2x+\lambda)} - A_v u\sqrt{\frac{2g(2x+\lambda)}{K+1}}\right), \tag{12}$$

where $x = L_u$ corresponds to the state, u is the control input defined by the opening of the valve, and $z := H_w^2 T_w$ is the combined exogenous input coming from the waves. Since we are interested in the revenue maximization of the WEC, we need to consider a suitable sampling time T_s that matches the market price and the input wave characteristics —availability, among others. Therefore, we discretize (12) using the forward Euler approximation, which can be written more compactly as

$$x_{k+1} = x_k + \Gamma\frac{z_k}{2x_k+\lambda} - \Omega u_k\sqrt{2x_k+\lambda}, \tag{13}$$

by introducing the constants $\Gamma := T_s \cdot \frac{1}{A_u}\frac{\eta\rho_{sw}gw_f}{64\pi\rho_c}$ and $\Omega := T_s \cdot \frac{1}{A_u}A_v\sqrt{\frac{2g}{K+1}}$, with the time step index $k \in \mathbb{N}_0$.

3 MODEL PREDICTIVE CONTROL STRATEGY

Model predictive control (MPC) is an optimization-based control strategy that is able to handle constraints explicitly and has been successfully applied to systems with complex dynamics (Maciejowski 2002, Camacho & Bordons 2013). MPC relies on predictions of the system dynamics, which are later used to formulate a constrained optimal control problem. Using these predictions, future occurrences can be considered in the optimization problem of a certain horizon. In the present, we use the dynamic lumped model described in Section 2. Consequently, after solving the optimization problem, only the first sequence is implemented. For the successive time steps, the optimization problem is solved again; this particular way of implementing the control law is called *receding horizon*.

As previously mentioned, MPC has been successfully applied to control WECs due to its inherent ability to optimize the energy capture while handling the system limitations. The proposed control strategy aims at maximizing the revenue obtained by the WEC. Hence, we define the WEC revenue $R_k := R_k(\xi_k, x_k, u_k)$ at time step k as

$$R_k = \xi_k\left(\rho_c g(2x_k+\lambda) - \frac{K_f\rho_c v_f^2}{2}\right)\eta_t Q_{v,k}(x_k,u_k), \tag{14}$$

for a given sampled price signal $\xi = \{\xi_0, \xi_1, \ldots\}$ corresponding to the intraday market, which is available one day in advance, and where $Q_{v,k}$ represents the draining rate at time step k. Note that the revenue in (14) is the product of the price and the power —including losses— generated by the WEC.

Accordingly, the revenue maximizing optimization problem can be formulated as

$$\max_{u\in U}\; J = \sum_{k=0}^{N} R_k,$$

$$\text{s.t.}\begin{cases} x(0) = x_0, \\ x_{k+1} = x_k + \Gamma\frac{z_k}{2x_k+\lambda} - \Omega u_k\sqrt{2x_k+\lambda}, \\ u_{\min} \le u_k \le u_{\max}, \end{cases} \tag{15}$$

over $U = \{u_0, \cdots, u_N\}$ for a horizon $N \in \mathbb{N}$. We denote the optimal solution of problem (15) as $U^\circ = \{u_0^\circ, \cdots, u_N^\circ\}$.

We remark that the optimization problem in (15) is non-linear and we need $J > 0$ such that it can be solved, which is the case here since $x, u > 0$ and we do not consider negative prices, i.e., $\xi > 0$. Due to the non-linearity of the dynamic model in (13), the explicit inclusion of the state constraints in the optimization problem is not straightforward. Thus, we incorporate them implicitly through the lower and upper bounds of the decision variable in the optimization problem. To constrain the upper bound on x, we let

$$u_{\min} = \begin{cases} 0, & \text{for } x_k < C, \\ 1, & \text{for } x_k \geq C; \end{cases} \tag{16}$$

on the other hand, for the lower bound on x we consider $u_{\max}$ in terms of the threshold hydraulic head

$$\bar{h}_k = h_{\min} + \frac{T_s}{A_u} Q_{p,k}, \tag{17}$$

that depends on the minimum head $h_{\min}$ and the pumping rate $Q_{p,k}$ at time step k, such that we let $u_{\max} = 1$ before the threshold is reached and use Torricelli's theorem (Faber 1995) otherwise; this is done to adapt $u_{\max}$ to the amount of remaining fluid in the reservoir, namely

$$u_{\max} = \begin{cases} \frac{2A_u\sqrt{h_k} + \frac{T_s}{A_u} Q_{p,k} - 2A_u\sqrt{\lambda}}{T_s A_v \sqrt{\frac{2g}{K}}}, & \text{for } h_k \leq \bar{h}_k, \\ 1, & \text{for } h_k > \bar{h}_k, \end{cases} \tag{18}$$

where h_k is the discretized hydraulic head in (5) at time step k.

Therefore, we rely on (16) and (18) to implicitly capture the constraints on the state x. An alternative to this would be to linearize the plant dynamics in (13) to express the constraints explicitly. The proposed MPC strategy for revenue maximization is presented in Algorithm 1 stated below.

Algorithm 1 Revenue maximizing MPC strategy

Inputs: ξ, H_w, T_w, x_0
Outputs: u, R

1: $z \leftarrow H_w^2 T_w$
2: **for** $k = 0, \cdots, T$ **do**
3: **calculate** $Q_{p,k}$ from (8) and $\bar{h}_k$ from (17)
4: **calculate** $u_{\min}$ with (16)
5: **calculate** $u_{\max}$ with (18)
6: **solve** problem (15) with $u \in [u_{\min}, u_{\max}]$
7: **return** $U^\circ = \{u_0^\circ, \cdots, u_N^\circ\}$
8: $u_k \leftarrow u_0^\circ$
9: **calculate** x_{k+1} with (13) and u_k, z_k
10: **return** $R(x_k, u_k, \xi_k)$ from (14)
11: **end for**

4 SIMULATION RESULTS

4.1 *Proposed MPC strategy*

The proposed control strategy described in Section 3, relies on the dynamic model presented in Section 2. The effectiveness of the strategy is illustrated by simulating the controlled system for 5 days. The used parameters are shown in Table 1, the wave data was taken from real data at buoys located in the coast near Ireland —buoys 62106 and 62092 (Data.marine.ie 2016)—, and the price was taken from the Irish wholesale market for electricity (Single Electricity Market Operator 2014). The intra-day price ξ and the exogenous input z, for high and low energy scenarios, are depicted in Figure 2 over a 5 day period.

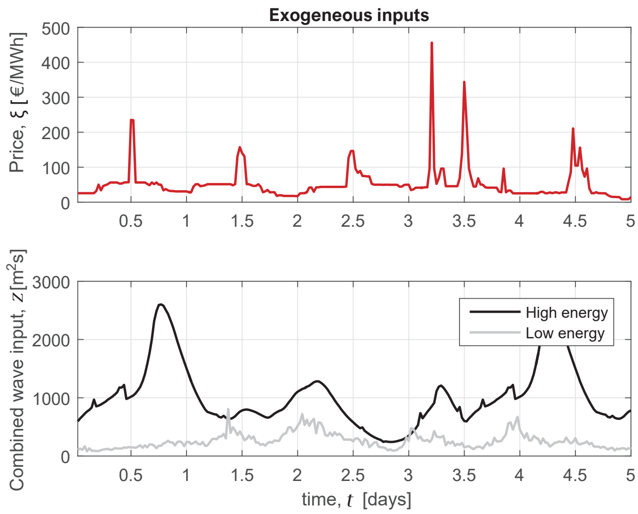

Figure 2: Exogenous inputs to the model: price and combined wave input for high energy scenario (buoy 62106) and low energy scenario (buoy 62092).

Table 1: Model parameters.

Parameter	Value	Description [units]
g	9.81	Gravitational acceleration [m/s^2]
ρ_{sw}	1035	Sea water density† [kg/m^3]
ρ_c	998.2	Cond. fluid density† [kg/m^3]
w_f	300	WEC wavefront [m]
A_u	60,000	Upper reservoir area [m^2]
L_c	100	Length between reservoirs [m]
$L_{u,0}$	0	Upper res. initial level [m]
$h_{\min}$	70.6	Minimum head [m]
C	40	Fluid capacity level [m]
μ_h	100	Average hydraulic head [m]
K_f	0.15	Friction loss coefficient [-]
η_p	0.9	Pumping efficiency [-]
η_m	0.9	Mechanical efficiency [-]
η_t	0.9	Turbine conversion efficiency [-]
A_v	38.48	Valve cross-sectional area [m^2]
v_f	10.8	Desired turbine flow speed [m/s]

† *at* $20°C$

The proposed control strategy described in Algorithm 1 was implemented in Matlab using the `fmincon` solver with a horizon $N = 48$ and a sampling time $T_s = 0.5$ hour; the results are depicted in Figure 3 for the high energy scenario, where the upper reservoir level $x = L_u$, the valve opening u, the price ξ and the revenue R are presented for a duration $T = 5$ days. In this paper, we assume that the delay between the opening of the valve and the conversion

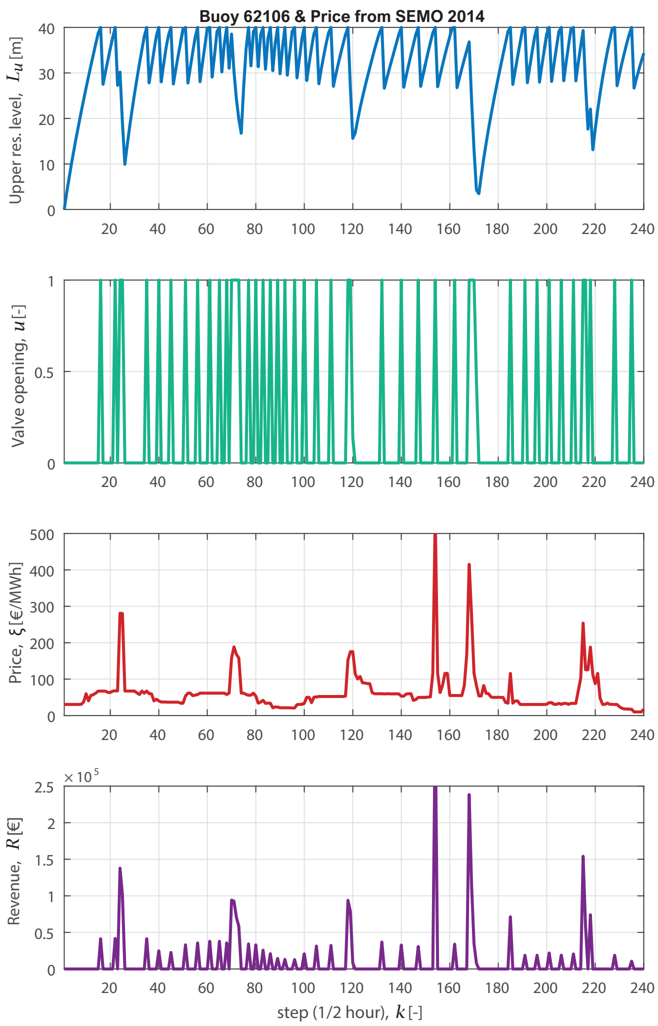

Figure 3: Results of the closed-loop simulation with the proposed control strategy and high energy wave input.

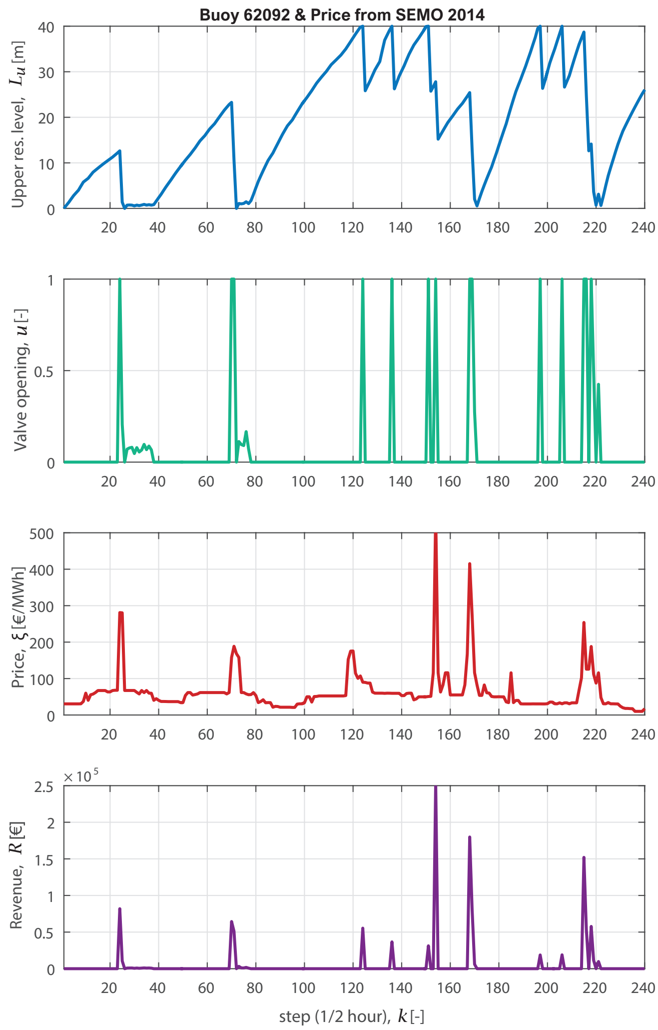

Figure 4: Results of the closed-loop simulation with the proposed control strategy and low energy wave input.

of the energy to electricity is negligible, and in any case much smaller than the chosen sampling time T_s.

In Figure 3, it can be observed that the Ocean Grazer WEC has a quicker draining rate with respect to the filling rate; this is a design choice to exploit better the storage capabilities of the WEC. Furthermore, it can be observed that the fluid level remains within the chosen bounds. Additionally, the opening of the valve corresponds to the instants where the price is high, and therefore the WEC can obtain more revenue. The former becomes clearer by comparing the revenue R against the price ξ, where it becomes evident that the control strategy makes the WEC open the valve (and produce electrical energy) during peak prices and otherwise keep the valve closed, earning no revenue but effectively making use of the WEC lossless storage.

Lastly, the results for the low energy scenario are presented in Figure 4, where it can be observed that the level of the WEC storage is closer to the lower bound with respect to the previous case, which also entails less opening of the valve and translates to less revenue, which is consistent with the energy content of the wave data, as shown in Figure 2.

4.2 *Comparison with different strategies*

In order to validate the proposed control strategy, we compare it —both for the low and high energy scenarios— with two other strategies, such that we consider three cases:

- Case 1 (C1): The proposed MPC strategy described in Algorithm 1.
- Case 2 (C2): A heuristic strategy that uses the storage of the WEC, which opens the valve when the price is above certain threshold price ξ_{th}. To guarantee that L_u will not go below its minimum, Toricelli's theorem was used to obtain the value of u to drain the reservoir when the hydraulic head is below the threshold $\bar{h}_k$.
- Case 3 (C3): No storage scenario, where the inflow surplus is curtailed, and the inflow deficit is compensated by suitably adjusting the opening degree of the valve u.

The comparisons between C1, C2 and C3 are reported in Figure 5 for the high energy scenario and in Figure 6 for the low energy scenario. In both Figures, the upper reservoir level $x = L_u$, the net flow $Q_p - Q_v$

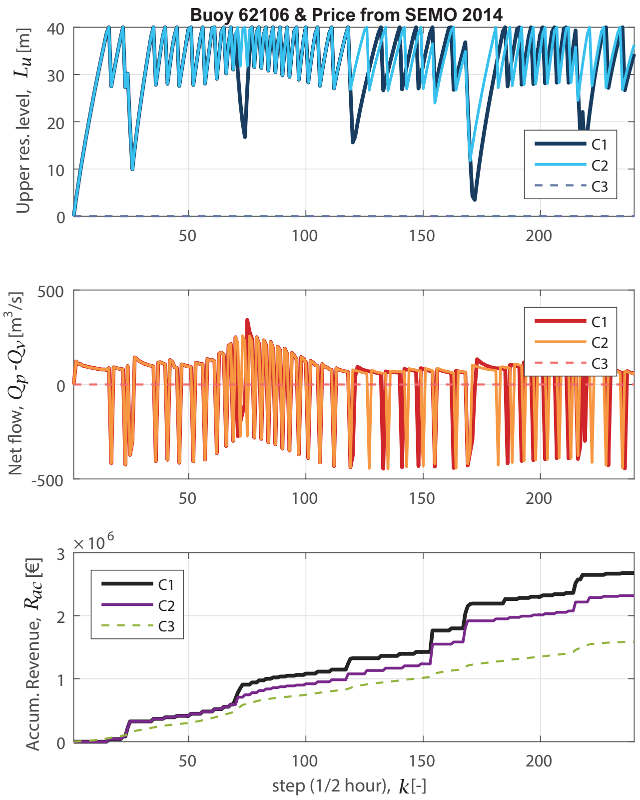

Figure 5: High energy scenario comparison. C1: proposed MPC strategy, C2: heuristic approach, and C3: no storage.

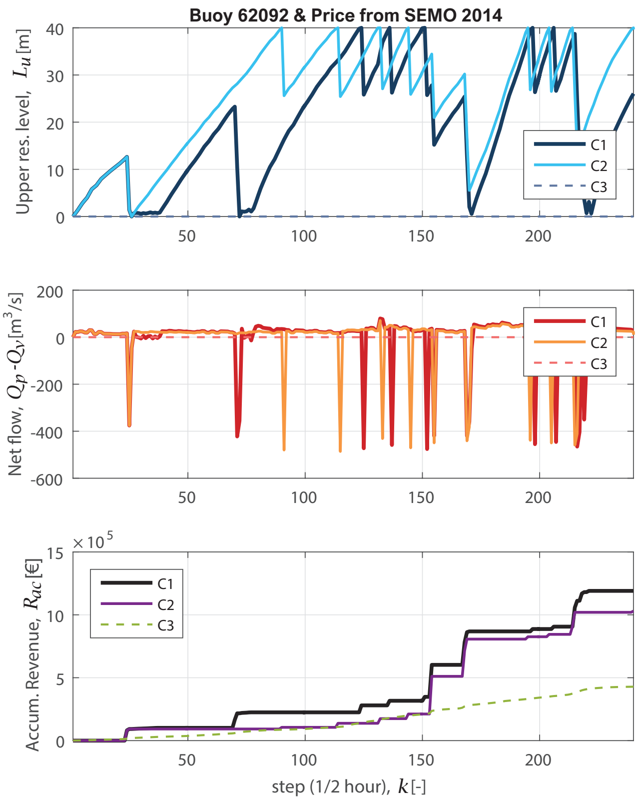

Figure 6: Low energy scenario comparison. C1: proposed MPC strategy, C2: heuristic approach, and C3: no storage.

and the accumulated revenue $R_{ac} := \sum_{k=0}^{T} R_k$ are presented.

Referring to Figures 5 and 6, it can be observed that the proposed strategy (C1) clearly outperforms the case where no storage is present (C3); this is caused by the fact that the WEC is not able to store potential energy to sell during the high price instances, since it is being forced to curtail the energy surplus and compensate for the deficit by producing less energy. Note that this is the case for many WECs and this illustrates the economical advantages of the lossless storage of the Ocean Grazer WEC. For the heuristic approach (C2), we let $\xi_{th} = 200$ €/MWh, and we can observe that it achieves intermediate results by making use of the lossless storage of the WEC, such that its better than C3 but not as good as C1. Taking C3 as the baseline, C2 increases the profit by 46.25% and 140.39% in the high and low energy scenarios, respectively; analogously, C1 improves by 68.93% and 177.66% in the high and low energy scenarios, respectively. Note that the impact of the lack of storage is more prominent for the low energy scenario.

5 CONCLUSIONS

In this paper we proposed a non-linear optimization based control strategy that maximizes the revenue of the Ocean Grazer WEC by exploiting its storage capabilities. This control strategy relies on predictions based on a net flow lumped dynamic model of the WEC, which characterizes the aggregated behavior of the WEC. Consequently, since it is a lumped model, transitory effects are averaged out. A limitation of the proposed strategy comes from the implicit inclusion of state constraints, which introduces certain degree of sub-optimality.

The applicability of the proposed predictive control strategy and its economic benefits were illustrated through simulation results, relying on wave and price data. Furthermore, the proposed strategy was compared against a heuristic approach using storage and a setting without storage, where it was shown that the proposed strategy effectively maximizes the total revenue. Future work involves the explicit inclusion of state constraints by linearizing the plant dynamics, and the analysis of the impact of different design choices in the WEC, such as turbine capacity and storage reservoir dimensions.

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