doi:10.3723/ut.32.003 Underwater Technology, Vol. 32, No. 1, pp. 3–13, 2014 www.sut.org

Society for Underwater Technology

Technical Paper

# Control strategies for oscillating water column wave energy converters

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*Received 10 May 2013; Accepted 23 December 2013*

## Abstract

The oscillating water column wave energy converter (OWC-WEC) is an established device which produces electricity by causing an ocean wave to drive air through a turbine.

A system to control the operation can improve the device's performance. In varying sea conditions, different objectives for control may be appropriate. For example, in some seas the controller might shut off the plant because the waves could damage the structure, while in others the controller should operate purely to maximise the energy passed to the electricity grid. The fundamentally nonlinear dynamics of the OWC-WEC influence the choice of control algorithm for the WEC.

Different outcomes in performance may be caused by very small changes in controller action. This is especially true for those OWC-WECs whose characteristics include stalling under certain conditions for optimal performance.

Robustness to uncertainty in inputs and prevention of damage to the structure are necessary. However, too much conservatism will lead to unnecessarily low extracted powers.

In the present paper, the advantages and disadvantages of feed-forward controllers and artificial neural networks previously used on OWC-WECs are discussed, as well as the testing of model predictive control and fuzzy logic controllers in the OWC-WEC context.

**Keywords:** Control, wave energy converters, oscillating water column

## 1. Introduction

An oscillating water column wave energy converter (OWC-WEC) is a device wherein a column of water is able to move within a chamber whose base is open to the sea and where the top of the column has air trapped above it. As the surface of the column of water moves, the air is forced in and out through a turbine for its power take-off (PTO; see Fig 1).

OWC-WECs can be sited at cliffs (Neumann et al., 2007; Arlitt et al., 2007) and breakwaters (Heath, 2007), or as offshore structures fixed to the seabed (Hong and Hong, 2012) or floating on a platform (Hotta et al., 1996). OWC-WECs may be positioned singly or in groups.

Single deployment is termed a 'point absorber' where the size of the device is small in comparison to the wavelength of the incident waves. If the OWC-WEC is formed of a series of OWC chambers across the wavefront, for example by inclusion within a breakwater, then this would be a 'terminator'. These terms come from their uses in wave behaviour in electromagnetism. Points and lines of OWC-WECs may be grouped together into arrays or farms. One advantage of point absorbers is that they have the potential to convert energy from waves approaching from many directions. The terminator, on the other hand, is particularly suitable for coast defence because the whole of a line of wave front may be blocked when using this type of deployment.

Obviously for WECs situated in close proximity, their influence on the surrounding water has a knock-on effect for the neighbouring devices, and much ongoing research is aimed at understanding this influence. For the design of WEC arrays, see Child and Venugopal (2010), Babarit (2010) and Weywada et al. (2012).

To avoid the complications involved in the use of non-return valves, the Wells turbine was designed for use in OWC-WECs (Tease et al., 2007). It rotates in the same sense under the effect of a pressure differential, no matter whether this differential is positive or negative, without the use of guide vanes (see Fig 2). However, the Wells turbine has poor stalling characteristics outside its main operating regime. This results in a large loss of power for airflows slightly larger than the optimal design

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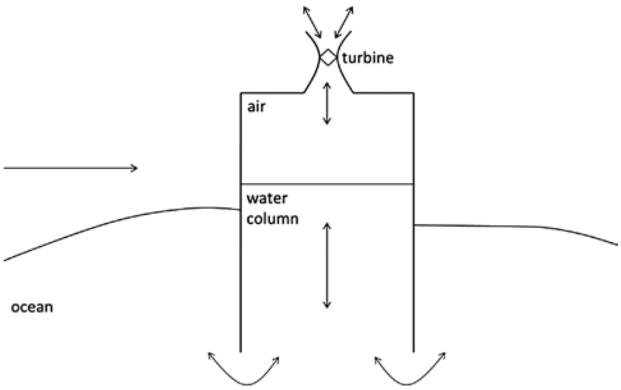


**Fig 1:** An oscillating water column wave energy converter (OWC-WEC). As the wave passes, the water column oscillates, forcing the air through the turbine

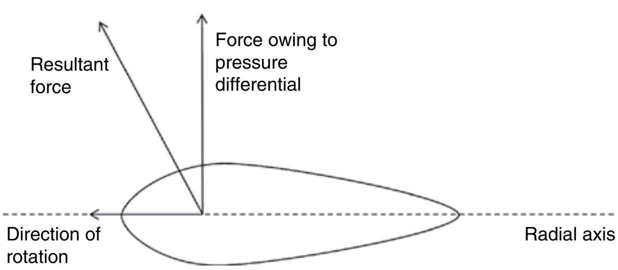


**Fig 2:** A Wells turbine blade

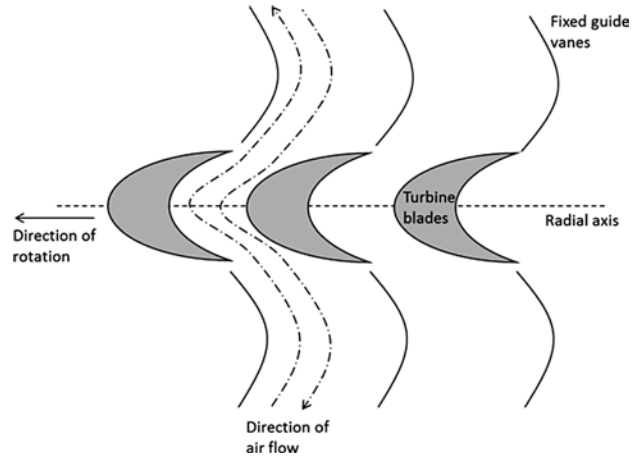


**Fig 3:** Impulse turbine with fixed guide vanes

conditions. This is clearly a problem for energy conversion, and thus control techniques that alter the properties of the turbine are considered as a way of avoiding such regimes. Other turbine types have therefore been investigated.

Impulse turbines with guide vanes, which generally give a smoother performance, may also be used (see Fig 3; Setoguchi and Takao, 2006). Explorations of radial turbines (Gato et al., 2012) and turbines with pitching blades (Cooper and Gareev, 2007) are also ongoing. Some of the pitching turbines use self-pitching blades whose blades are free to move, while others use active control. Any turbine in which the movement of the blades may be controlled should lead to improved energy conversion, although the turbine must be designed so that the continuous movement does not cause excessive damage through fatigue. In addition, control should only be used in a way that increases net energy conversion.

There are also other Wells configurations which allow for pitching about the nose of the turbine (the trailing edge being the part that moves). This can prevent stalling as the critical angle of attack can be avoided by the changing pitch angle, rather than by speeding up the turbine.

Control of any system is based on what can be measured about the system and what may be changed. For the OWC-WEC, it may generally be possible to measure pressure difference, flow through the turbine, turbine speed, applied torque and output energy. Wave height or proxies for wave height such as pressure on the seabed, as well as the position of any valves, may also be measured.

It is possible to control the power take-off (PTO) settings in the form of generator slip and torque, and thus the turbine speed. Valve control (whether bypass or shut-off) for both abrupt on/off options and softer changes should be possible. The aim is then to keep the turbine operating effectively for generation (avoiding stall, but without being too conservative). Thus the turbine frequency, generator torque and valve position should match the pressure difference and flow through the turbine.

The particular interest in control is attributable to the scope for cost effectiveness in comparison to any equipment required for its operation. In fact, the equipment may be a requirement for general device operation no matter the control strategy chosen, and control systems will certainly be required for failure prevention in large seas. In addition, unlike for the geometry of the WEC, the controller may be updated after deployment without the need to build and install new structures. In fact, it is possible to continue to update it or try new controllers long after initial operation.

Sometimes control for WECs is formulated with the incident wave as an unknown disturbance (Valério et al., 2008; Cross et al. 2011). While this is helpful, it suggests that the same motion is required no matter the wave. This can be good for small WECs where it may be assumed that operation is largely within the limited/end-stop regime. For a large WEC, however, the disturbance formulation may be misleading as, more broadly, the present wave characteristics need to be tracked rather than removed. This tracking behaviour is the case for most OWCs, where using limited motion as the standard operation would cause damage to the device.

## 2. OWC-WEC control methods

There are a number of methods that have been used previously for OWC-WEC control, some of which are in related areas that could provide an insight into the problem. Historically, optimisation work for WECs has mostly been done in the frequency domain. This requires a linear system in which superposition holds. For a device with dynamic structures of constant mass moving with small amplitude, this is a good assumption. However, for an OWC-WEC which features hysteresis in its air chamber, the time domain is the more viable option.

The classic frequency domain description is elucidated initially, as this is where the original research began. Then latching is described and finally the approaches which use continuous time-domain techniques are discussed.

### *2.1. Dynamics of an OWC*

For regular (sinusoidal, Airy) waves, the dynamics may be framed as simple harmonic motion in the frequency domain, with the vertical motion of the water column denoted by $X$ and the angular frequency by $\omega$ (see Falcão et al., 2012). As such, terms involving the vertical velocity of the column will be given by $i\omega X$, and those involving acceleration by $-\omega^2 X$. Thus:

$$-\omega^2 MX + i\omega BX - \rho g A_{col} X = F_e + A_{col} \backslash \Delta p_{cham} \tag{1}$$

shows that a mass ($M$) is accelerated with damping ($B$), and spring constant ($\rho g A_{col}$) by a force equal to $F_e + A_{col}\backslash\Delta p_{cham}$, where $F_e$ is excitation force and $A_{col}\backslash\Delta p_{cham}$ is the area of the column multiplied by the air pressure difference above the water – the term is the pressure force on the column. The hydrodynamic variables are outlined in Fig 4. The mass ($M$) is given by the sum of the mass of water making up the column and the added mass, which is a term used to describe the apparent additional motion proportional to acceleration caused by motion in a fluid. The mass is assumed not to be a function of time. For the OWC, because the volume of water in the column will change as the water surface moves, the definition of an unchanging mass is debateable. However, for small motions this approximation is valid and usual.

#### 2.1.1. Excitation force

When looking at any device being bombarded by waves, the excitation, diffraction and radiation must be investigated.

The wave excitation forces ($F_e$) are the easiest of these three to visualise. The excitation comes simply from the sum of the pressures acting on a structure (or in the case of the OWC, acting upon the water column), as shown in Fig 4. It should be noted that this excitation force is not generally proportional simply to the displacement of the wave.

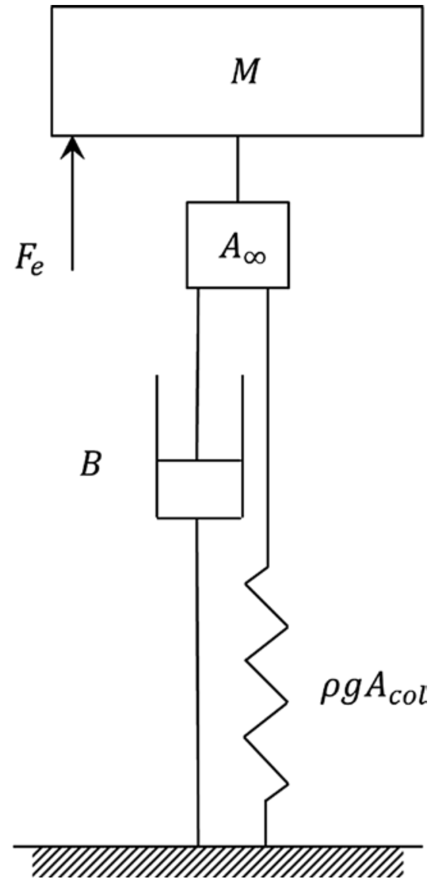


**Fig 4:** The hydrodynamics of the OWC modelled as a mass-spring-damper system

#### 2.1.2. Radiation and diffraction

The radiated wave is that which is created by the mass moving in still water. For the case of the OWC, this should more accurately be stated as being the wave created by the changing of the pressure in the chamber while in still water. This wave radiates energy and thus loses it from the device. The radiation can thus be considered as a damping term proportional to velocity. In Equation 1, this is given by $B$.

The damping values for each frequency may be calculated analytically for the simplest geometries (Evans and Porter, 1995), or using WAMIT, AquaDyn or ANSYS® AQWA™ for more complicated shapes.

Because at infinite frequency there would be radiation, a radiation term is generated that is proportional to mass, as well as the entrained or added mass. The radiation term has different values at different frequencies, owing to the apparent additional mass which must be moved with any structure when moving in a fluid. This extra mass-like term owing to the radiation is sometimes denoted by $M_\infty$ or $A_\infty$ (as in Fig 4) to show that the term is like the added mass, but is generated by the infinite-frequency part of the dynamics.

The diffraction is the force caused by the interaction of the structure, if fixed into position, with the incident wave. This term is sometimes incorporated into the excitation force and will be important when the OWC is large in comparison to the wave or wavefront, for example when a breakwater structure is considered.

#### 2.1.3. Buoyancy

The spring term ($\rho g A_{col}$) is owing to the buoyancy of the device or the tendency of the water to return to its original position because of gravity. $\rho$ is the density of the water, $g$ is the gravitational acceleration and $A_{col}$ is the area of the water column. This assumes that the area of the water column does not change in the vertical direction and that all of the motion is in the vertical direction. This is the case for a structure like that shown in Fig 1.

#### 2.1.4. Chamber pressure

Along with the force owing to the waves, a force will be applied to the surface of the water column proportional to the pressure difference between the air in the chamber and that of the atmosphere around the OWC.

Equation 1 describes the motion of the water surface, but this is coupled to the thermodynamics of the air. As described in section 1, in an OWC the power is extracted by a turbine. In Falcão et al. (2012), the turbine is defined by a pressure differential:

$$\Delta p_{cham} = \frac{-k_1 \dot{m}}{\rho_{atm}} \tag{2}$$

where $k_1$ is the turbine constant defined as the ratio of the non-dimensional pressure to the flow coefficient; $\dot{m}$ is the mass flow out of the chamber per area of turbine; and $\rho_{atm}$ is the density of the air that is to be assumed constant. The units of $k_1$ are $\mathrm{kgm^{-2}s^{-1}}$. Note that the turbine constant is a function of the incident wave frequency, but not a function of time – that is, the incident wave is assumed to be a single frequency and never change. Thus, the best value to use for that frequency is assumed to be used, and once chosen is never to change.

### *2.2. Optimal turbine constant in single frequency waves*

Using this fixed value of $k_1$, an ideal value can be found that maximises the power absorbed by the WEC. The power absorbed by the turbine is then given by:

$$P_{turb} = \frac{\Delta p_{cham}^2}{k_1} \tag{3}$$

and sinusoidal motions are assumed. Therefore, for the ideal case where the air moves isentropically and incompressibly, the average power absorbed by the turbine is:

$$\widehat{P_{turb}} = \frac{|\Delta p_{cham}|^2}{2k_1}. \tag{4}$$

This average power is also equal to:

$$\widehat{P_{turb}} = \frac{|F_e|^2}{8B} - \frac{B}{2}\left| i\omega X - \frac{F_e}{2B}\right|^2 \tag{5}$$

where $|\cdot|^2$ indicates modulus squared. In order to maximise this power absorbed by the turbine, the right-hand term should equal zero. Thus,

$$X = \frac{-iF_e}{2\omega B} \tag{6}$$

which can be substituted into the equation of motion (Equation 1) so as to find $k_1$, the turbine constant:

$$k_1 = \frac{\left[\omega^2 M + \rho g A_{col}\right]^2 + \omega^2 B^2}{\omega^2 A_{col}^2 B} \tag{7}$$

Note again that $k_1$ is a function of frequency, but not of time, so that for each frequency there is an optimal value of $k_1$ based on the assumption that the incident wave is a sine wave which continues for all time.

It is thus possible to use a value for the turbine coefficient that is ideal for each of the various frequencies, as shown in Fig 5. In this case, feedback is unnecessary because the system is assumed to be ideal. These types of reference-based controllers for OWCs may be called feed-forward.

### *2.3. Control in the frequency domain (complex conjugate control)*

The control rule of Equation 7 is the case for single frequency incident waves. For waves made up of a sum of sinusoidal waves defined by some spectrum, the model can be set up in the frequency domain. However, in this case, the coefficients in Equation 1 are in fact functions of frequency (Falnes, 2002; Price, 2009; Alves et al., 2011). Rather than being given by the multiplication ($i\omega BX$) as in the single frequency case, the radiation force becomes more

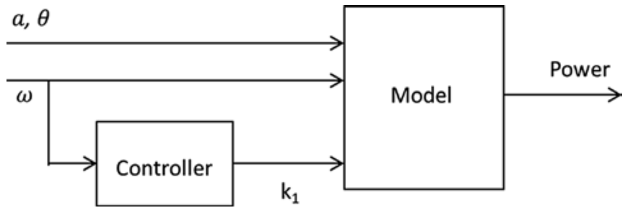


**Fig 5:** A feed-forward controller operating for single frequency sine waves that gives a damping coefficient to a model OWC

complicated. This is because both $B$ and $X$ are functions of frequency and so now there is a convolution. Thus the radiation force may be defined as:

$$\begin{aligned} F_{rad}(t) &= F^{-1}\{i\omega X(\omega) * K(\omega)\} \\ &= A_\infty X(t) - \int_0^t K(t-\tau)X(\tau)d\tau \end{aligned} \tag{8}$$

where $K$ is made up of an added mass term and a damping term:

$$K(\omega) = i\omega A(\omega) + B(\omega) \tag{9}$$

with $B(\omega)$ denoting the frequency-dependent damping coefficient and $A(\omega)$ denoting the frequency-dependent added mass coefficient, where

$$\begin{aligned} B(\omega) &= \int_0^\infty K(t)\cos \omega t \, dt \\ A(\omega) &= A_\infty - \frac{1}{\omega}\int_0^\infty K(t)\sin \omega t \, dt \end{aligned} \tag{10}$$

This means that the terms in Equation 1 become:

$$\begin{aligned} &-\omega^2(M(\omega)) + A_\infty) * X(\omega) \\ &+ i\omega B(\omega) * X(\omega) \\ &- \rho g A_{col} X(\omega) \\ &= F_e(\omega) + A_{col}\Delta p_{cham} \end{aligned} \tag{11}$$

Equation 11 is the model of the system, but in order to take maximum power from the system, the controller should regulate the pressure to match both the real and imaginary parts of the right hand side of Equation 12:

$$\begin{aligned} \Delta p_{cham} = \frac{1}{A_{col}}\{&[-\omega^2(M(\omega) + A_\infty) \\ &- \rho g A_{col}] * X(\omega) \\ &+ i\omega B(\omega) * X(\omega) \\ &- F_e(\omega)\} \end{aligned} \tag{12}$$

It should also be noted that, again, the mass cannot change as a function of time; it can be a function of frequency, $M(\omega)$, but not a function of $X$. Also of note is that the terms on the right-hand side need to be measureable or calculable for this control to work optimally. This is not at all straightforward because of the various convolutions involved. It is thus essential to move into calculation in the time domain.

### *2.4. Latching*

No discussion of control for an OWC would be complete without including latching control (see, e.g., Korde (2002); Eidsmoen (1998); Babarit and Clément (2005)). In latching control, the WEC is fixed into position when it reaches zero velocity and is released some time later. Clearly, the moment to release is thus an important control variable, with the aim being to choose a suitable phase match to produce maximum energy from the WEC.

With latching control, no work has to be supplied to damp or accelerate the motion, so no reactive energy is needed from the grid. However, the action of throwing the latch on or off requires energy. Such a structure must therefore be able to hold the WEC against the sea, which requires sturdy construction and can have implications for cost and reliability.

The moment to unlatch may be determined using several strategies, so the latching principle may be grouped within many of the techniques described in the sections that follow. Unlatching time could be a constant fixed on initial operation, and could be based on crossing some threshold or on choosing the optimum moment using a predictive model of the WEC (Babarit and Clément, 2005; Lopes et al., 2009; Hals et al., 2011b).

In the case of the buoy-type WEC, the buoy itself is held in position relative to some external reference. For the OWC-WEC, the water column cannot directly be held in position. Consider, however, the water column rising to its furthest point during an oscillation. A shut-off valve between the chamber and the turbine may be fully closed so that the air cannot escape the chamber (Lopes et al., 2009). This results in the column of water being suspended by the suction of the air. If the shut-off valve is then reopened once the surrounding water level has dropped, air will be sucked into the chamber through the turbine more swiftly than would otherwise have been the case as the water column falls.

Similar arguments may be made for latching at the trough of water column displacement. Depending on the operation of the turbine in the OWC-WEC, this may be beneficial. Again, however, the energy required to move such a valve frequently under real conditions will be very large. Thus, the complications involving the use and reliability of valves return, and such valves were removed in the turbine designs of the last few decades.

Another point to note is that the spring characteristics of the air chamber cause fluctuations in the pressure within the chamber (Lopes et al., 2009), and the flow of air through the turbine will be interrupted from its usual path by the frequent movement of the valve. The major drawback, however, will be the very large forces that act on the latched machinery, requiring a heavy-duty system to be designed and implemented.

### *2.5. Control in the time domain*

Control in the frequency domain is a reasonable approach when the PTO is linear. However, for an OWC the turbine will have significant nonlinearities, especially in the case of stalling events for the Wells turbine. Other nonlinearities are also included in the hydrodynamics, where the linear representations are only the case for small motions, and for a complete picture of the thermodynamics. Thus, control action designed for the time domain has the potential to include the operation of a PTO in a way that no frequency domain description can achieve.

Alves et al. (2011) explored the time domain approach, using it as a way of producing a reference signal. In the time domain, the radiation damping representation seeks to extend Equation 8 and its convolution. They deal with this by approximating the frequency domain transfer function from incident wave amplitude to damping by a state-space model, so that the radiation damping force:

$$y = \int_0^t K(t-\tau)\dot{\xi}(\tau)d\tau \tag{13}$$

is represented by the two equations:

$$\begin{aligned} \dot{x}(t) &= Ax(t) + B\dot{\xi}(t) \\ y(t) &= Cx(t) \end{aligned} \tag{14}$$

where $x(t)$ is a particular state of the system (rather than the displacement of the water column surface).

From thermodynamics and assuming an isentropic process, the relationship between the pressure and density of the air is:

$$p\rho^{-\gamma} = p_0\rho_0^{-\gamma} \tag{15}$$

where $\gamma$ is the standard adiabatic index; $p$ is the absolute pressure in the chamber; $\rho$ is the density of the air within the chamber; and $p_0$, $\rho_0$ are the initial values of these variables.

The thermodynamics may be combined with the state-space model of the water surface dynamics, using the pressure as an extra state of the system. Thus $x(t)$ becomes:

$$x(t) = [x(t)\ \ \xi(t)\ \ p(t)]^T \tag{16}$$

The turbine is assumed to be represented as the ratio of the non-dimensional pressure to the flow coefficient as before:

$$k_2 = \frac{\psi}{\phi} \tag{17}$$

The subscript '2' indicates the second treatment of the turbine constant. However, for this setup, the turbine is calculated as:

$$k_2 = \frac{pD}{\dot{m}N} \tag{18}$$

where $p$ is the absolute chamber pressure (not that relative to atmosphere) and where $D$ is the diameter of the turbine. The mass flow is given by:

$$\dot{m} = \frac{D}{Nk_2}\Delta p_{cham} \tag{19}$$

where $\Delta p_{cham}$ is the difference between the chamber pressure and the atmospheric pressure, as before.

In Alves et al. (2011), it is interesting to see that the turbine constant ($k$) can be a function of time, as not only the pressure and the mass flow, but also the speed of rotation of the turbine are allowed to change. However, in their paper the model is only tested against single frequency, regular wave data from WAMIT, and no change in turbine damping is investigated.

To look at the difference in power caused by using different turbine coefficients ($k$), Nunes et al. (2011) made OWC models with different turbine coefficients for various sinusoidal waves:

$$\dot{m} = \frac{\varphi_\psi r_{turb}}{N(t)}\Delta p_{cham} \tag{20}$$

and

$$k_3 = \frac{\varphi_\psi r_{turb}}{N(t)} \tag{21}$$

The flow coefficient ($\varphi_\psi$) is assumed to be 1.8 and the turbine radius ($r_{turb}$) is 1m. Thus $k_3$ is assumed to be a function of $N(t)$ only.

Transfer functions to describe the airflow and the pressure changes were found, assuming $k_3$ values that are constant in time. These transfer functions map the incident wave height of a sinusoid to these thermodynamic properties. As the air-flow

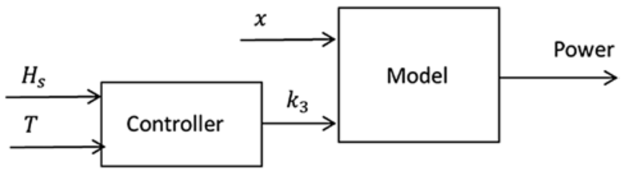


**Fig 6:** The first control logic used by Nunes et al. (2011)

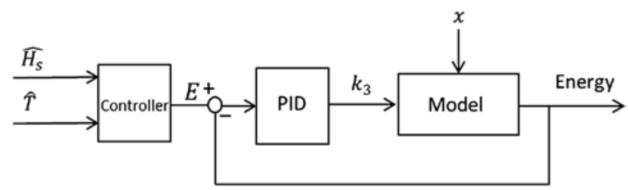


**Fig 7:** The second control logic used by Nunes et al. (2011). This is based on the same control approach as in Fig 6, but the wave height and period come from an estimate into the future, and a proportional integral derivative (PID) controller is used to try to get a more accurate and smooth output. A PID controller is a standard controller used throughout all types of industrial design

and the pressure differential may be multiplied to approximate the output power, the value of $k_3$ that leads to the greatest energy conversion may be selected for each frequency.

For wave conditions given by a spectrum, the frequency of the expected spectral peak is used to choose $k_3$. These functions were used to build the controller shown in Fig 6. This controller is similar to that shown in Fig 5, as it is a feed-forward controller that takes the wave properties and generates a reference turbine coefficient. The wave properties must be known ahead of time.

Producing the maximum power, however, may not be the most appropriate control action for all wave conditions. For larger seas, the water level may go beyond the geometrical limits of the WEC, causing damage to the structure. In order to avoid such conditions, another set of transfer functions were generated. These looked at the mapping from the incident wave height to the displacement of the water column. Thus, the value of $k_3$ which maximised the movement of the water column at each incident wave frequency could be found.

Crucially, the transfer functions mapping the incident wave height to the displacement also enabled the identification of the value of $k_3$ which maximised the output power without having the motion go beyond the end points. For wave conditions in which the water column would move beyond these limits regardless of value of turbine coefficient applied, the OWC was assumed to be in 'survivability mode' with zero power output. It should be noted that the possibility of stalling was not considered as part of this study. Increasing the range of seas in which the OWC does not have to be in survivability mode increased the power supplied to the grid significantly.

The work by Nunes et al. (2011) goes on to consider the use of a proportional integral derivative (PID) controller in a feedback loop to specify the expected output energy over a time window and adjust the value of $k_3$ in order to match this. This is shown in Fig 7. The range of available turbine coefficients was larger than could readily be achieved for a real turbine, and no cost was associated with changing them. Thus the study produces an overestimate of the possible smoothing using this technique. However, the strength of even simple controllers was demonstrated.

It should be noted, however, that the controller shown in Fig 7 requires an estimate of the significant wave height and period ($\widehat{H_s}$ and $\hat{T}$). This was generated by using a fast Fourier transform (FFT) over a short time window predicted into the future. This requires more processing than having only the instantaneous information, but the prediction is available and has the potential to be quite accurate. More details are given of future wave prediction in section 2.7.

For sinusoidal waves, an initial experiment was made using a PID controller to try to achieve phase and amplitude control described in Equation 7, wherein the aim is to have the pressure difference in-phase with the wave excitation The parameter that is changed is the mass flow ($\dot{m}$) in Equation 20, which has an additional constant, such that:

$$\dot{m} = k_3 \Delta p + \alpha(t) \tag{22}$$

No limits were put on $\alpha(t)$. This proved successful for regular waves, but was not as effective as the uncontrolled case for irregular waves. This may be owing to the simplicity of the controller.

## *2.6. Modern control and hybrid techniques*

### 2.6.1. Artificial neural networks

In addition to using latching or a constant turbine coefficient, the rotational speed of the turbine may also be altered. This is particularly useful for avoiding stalling of the Wells turbine (Amundarain et al., 2010). Clearly, stall avoidance techniques may only be applied in the time domain.

Stall occurs when the airflow rate rises above a certain critical value. This rate may be avoided if the turbine is allowed to speed up for waves that produce large pressure differences.

The best values of turbine speed for given incident pressure variations were found by Amundarain et al. (2011) by using laboratory experiments in which a Wells turbine was driven by a sinusoidally varying pressure difference. The aim was to maximise the pressure drop across the turbine without entering the stalling regime. Along with using this offline dataset as a rule set to interpolate over, they used an artificial neural network (ANN) to implement this strategy.

ANNs are designed for just such nonlinear systems and processes (Bose, 2007). They use a group of function approximators to model the dynamics. Test data are used to train the network so that it can match inputs and outputs. Iterative changes are made to the weights and biases of the functions so that the network matches the pairs of inputs and outputs more effectively. It is important not to overtrain the network, otherwise it will match only a particular dataset rather than the underlying physics of the system.

Defining the pairs of inputs and outputs from the real data to use as a match for the device's operation is a complicated process. The effects of the control action in use when the data were developed are what the ANN model will generate for future operation, even when this control action is no longer acting. Thus, use of a controller close to the optimal situation for whichever scheme is under investigation would be wise for operational use during test data production. However, the ANN may be updated as the controller is developed (Price et al., 2005).

Training a network generally takes some time and is thus performed offline. The choice of how frequently to update the ANN model will depend on the behaviour of the WEC and the changeability of the wave climate. The ANN to use could be swapped according to the season or trained to correspond to the most recent 10min of data, for example. The transition from one model to another should be made at least as smoothly as the action caused by any other controller operation.

The control loop used by Amundarain et al. (2011) is shown in Fig 8. The network uses the pressure differential to generate the appropriate value of turbine speed (in fact, the allowable slip of the generator).

While the reference values to match were generated by Amundarain et al. for sinusoidal pressure variations, their effectiveness was also tested with irregular pressure variations. These references proved to be effective in preventing stall and thus increasing overall power output in comparison to a fixed value for the generator speed.

ANNs have been used elsewhere in WEC control (Beir et al., 2007; Valério et al., 2008). Different architectures have been used to try to remove some of the difficulty associated with the ANN being trained only on the data available, for example architectures which have feedback loops within the

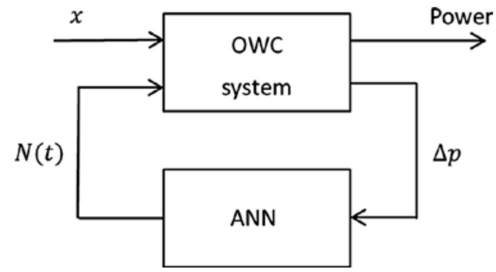


**Fig 8:** The control loop as implemented in Amundarain et al. (2011). Note that the OWC system block includes the generator. More focus is placed in this research on having the generator behave as instructed, rather than on what that instruction should be

controller, rather than solely through the system. Because the ANN is used for maximum power, it may well be combined with a higher level controller for survivability control. It is possible to include this as requirement in network training, by introducing penalties for extreme motions, for example, but this may lead to conservative responses during normal operation.

### 2.6.2. Model predictive control

In section 2.5, time-domain control using $k_3$ was considered in which the properties of the turbine were allowed to vary. This was set up so that it was part of a model predictive control (MPC) controller, as described in Fig 9. In this figure, $k_3$ has been turned into $T_g$, the torque on the generator.

In theory, MPC gives the best results for maximisation of energy under some constraints. Because of the predictive element, it can begin to apply control before the limits are reached. In addition, at each time step the controller calculates for future possibilities and chooses the action for the current time step most likely to result in the largest energy over the future time window.

The control action in MPC is like a chess player sacrificing pieces (energy) in the current move (time step) to gain more in future moves. The strategy is based on expectation of the way the opponent will respond (the motion of the water surface and the OWC). Therefore, a controller that looks only for maximum energy, which requires another controller to come into play at the limits, will not be able to reach such high energies as an MPC controller which calculates using the assumption of limits. It can also be successful because the model used to describe the system in MPC does not need to be a linear one, although the calculation speed may be significantly increased unless it is.

MPC has also been used for buoy-like WECs by Cretel et al. (2010) and Hals et al. (2011a,b). The

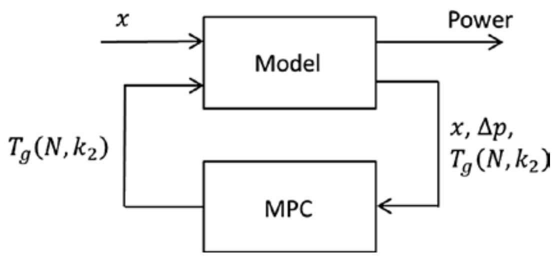


**Fig 9:** Implementation of an MPC controller as described by Alves et al. (2011). $T_g$, the generator torque, is used as the control variable and is a function of the rotor speed and the turbine coefficient

motions of these buoys and their modelled PTOs are more realistically linear than is the case for OWCs.

The drawback of MPC is that the model of the system must be accurate for the controller to provide the best action. However, when an accurate model is available, the technique may be very successful owing to the potential for inclusion of non-linear behaviour, the use of prediction in the input and response and the ability to deal with limits while controlling for total maximum energy.

### 2.6.3. Fuzzy logic

A technique that gets around the difficulty of having a precisely accurate model is fuzzy logic (Jang et al., 1997). Here, the controller consists of a set of rules that have different strengths of impact depending on how far through the range of possibilities a variable is deemed to be.

A fuzzy logic controller was used on an ideal spherical semi-submerged buoy by Schoen and Moan (2008) and extended for robustness in Schoen et al. (2008). In a fuzzy logic controller, the various scenarios are represented by rules that are combined together. Owing to uncertainty in the modelling, no assumption of perfect decision-making is assumed. Instead, in effect the controller works out how likely the various possibilities are and estimates what would be an appropriate strategy.

One of the major advantages of a fuzzy logic controller is that the variables correspond to real parameters. Thus for extreme motion, the controller will naturally apply the same sort of control as with the rest of the large motions, so no unexpected behaviour is likely.

As with ANNs and MPC, a fuzzy logic controller can take multiple inputs and map them to multiple outputs. The fuzzy controller can include the survivability limits as described in sections 2.5 and 2.6.1, meaning that it can combine control objectives. Of course, the control rules need to be trained offline by some genetic algorithm, for example (see Gunn et al., 2009), although they can be updated after some duration. However, this means that the controller will only be as good as the data selected. Because the controller is based on rules and sets rather than equations and gradients, there is no guarantee of a perfect solution. That said, the advantages of fuzzy logic, where the rules and parameters correspond to physical variables and no ideal model system is required, suggest that it is a very worthwhile technique to try at this stage.

## *2.7. Control using advanced information*

Given that the response will not be instantaneous, prediction of the pressure some way into the future is advantageous, and is an important part of MPC. Much research has been undertaken into prediction of the future waves using either recent wave data (Price and Wallace, 2007; Fusco and Ringwood, 2010) or nearby wave data (Belmont et al., 2006; Belmont, 2010). Much of this is in the context of requirements for phase and amplitude control coefficients. If just a short interval into the future is required, this should be within the coherence time of the wave, and thus one (or a combination) of polynomial curve fitting (Fusco and Ringwood, 2010) or orthogonal basis function (Schoen et al., 2011), low pass filtering/sine coefficient fitting or an ANN may be the appropriate tool. The one that is best will be dependent on the interval and the nature of the sea state.

The prediction of the wave or pressure would usually be included in any ANN model as previous data points are used as part of the model. The number of these previous data points is crucial to the effectiveness of the ANN (Valério et al., 2008). It is important to include the recent dynamics which will affect the upcoming behaviour, but reaching further back will not necessarily provide information with any relevance.

## *2.8. Further requirements and future developments*

In the present work, no attempt is made to include control for power smoothing or fault tolerance (Alberdi et al., 2012). The importance of plant availability (Teillant et al., 2012) is also only briefly mentioned.

As the device will take some time to respond, the controller should not assume that the control action is instantaneous (Cross et al., 2011). This delay (and ideally the form the delay takes) should be included in the model.

The action taken by the controller leads to an effect which continues for some time into the future. This implies a certain duration of influence, which gives the length of time that the current time step's optimisation should consider.

If some kind of switching is involved, then the moment to switch will have been tuned beforehand on some datasets. With switching, the action of switching from one model to another should produce jumps no greater than those generally seen as part of the controller. A smoothing method may be required to achieve this. If switching is used, hierarchical control is inevitably being used. The switching (top level) controller must be able to calculate the implications of moving between each of the lower level controllers.

## 3. Conclusion

The nature of an OWC-WEC means that it is nonlinear. This is particularly pronounced for operation in large, powerful seas. As such, this should be included in the control methods from the initial design stage.

OWC-WEC control, like for many other machines, requires compromise. In this case, the incentives for greater energy conversion are balanced by the need to avoid stall of the turbine and damage to the device.

Owing to imperfect actuators at the low level and limits/switching at the high level, hierarchical control should be considered as inherent within the system and therefore incorporated into the design.

A system with rules of some kind will be necessary in large seas. Although a nonlinear MPC controller is ideal for this task, the models of OWCs are not accurate enough to provide robust control, thus a fuzzy logic controller is to be preferred at this stage.

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