Evolutionary Algorithms for the Development and Optimisation of Wave Energy Converter Control Systems

K. Gunn[1], C.J. Taylor[1] and C. Lingwood[1]

[1]Engineering Department,
Lancaster University,
Lancaster, LA1 4YR
E-mail: k.gunn@lancaster.ac.uk

Abstract

Many strategies have been proposed for the control of wave energy converters (WECs). In order to evaluate these control strategies, they need to be optimised for realistic operating conditions. This paper develops a generic approach for WEC optimisation based on the use of Evolutionary Algorithms (EAs). A new evolutionary algorithm is developed to efficiently resolve problems found in WEC control. Simulation results are presented for tuning an illustrative device in both sinusoidal and real waves; and for optimisation of 'slow tuning', 'latching' and 'fast tuning' control systems. These results show an increase in the power capture of the device using the optimised control, and demonstrate a convergence to an optimum solution within the constraints presented. In contrast to conventional methods, the proposed EA successfully optimises the control algorithms for realistic seas without prior assumptions. The capabilities of EAs in a "machine learning" setting, in which the control algorithm continues to evolve after installation, are then considered.

Keywords: Wave Energy Converters, Optimisation, Evolutionary Algorithm, Latching, Control

Nomenclature

CWR = Capture Width Ratio
WEC = Wave Energy Converter
EA = Evolutionary Algorithm
ANN = Artificial Neural Network
PTO = Power Take Off

Model

ω = Angular frequency of the incoming waves (rad/s)
ξ = Complex displacement amplitude (m)
λ = Wave Length (m)
$\mathbf{A}$ = Added mass (kg)
$\mathbf{B}$ = Radiation damping coefficient (Nsm^{-1})
$\mathbf{C}$ = Hydrodynamic stiffness (Nm^{-1})
$\mathbf{F}$ = Wave excitation force (N)
$\mathbf{X}$ = Collector displacement (m)
B = Damping coefficient (Nsm^{-1})
C = Spring coefficient (Nm^{-1})
F = Force (N)
S = Binary state
T = Period (s)
P = Power (W)

Subscripts

ω = At angular frequency of
B = Damping
C = Spring
L = Latch
A = Externally applied
t = Total

Superscripts

. = First derivative

$$- = \text{Mean over} \begin{cases} \text{one period} & \text{Regular waves} \\ \text{one set} & \text{Irregular waves} \end{cases}$$

Evolutionary Algorithm

L = Length of decision vector (dimensionality)
$\mathbf{x}$ = Decision vector of offspring
$\mathbf{y}$ = Decision vector of parent or Spartan
r = Gaussian random number (0 mean and standard deviation of 1)
σ = User definable EA variable
s_i = Significance index

Subscripts

n = n^{th} parent
m = Mother
x = Offspring
s = Spartan

1 Introduction

Increasing concern over energy supply and climate change have resulted in substantial research into wave energy converters (WECs). In attempting to maximise the energy captured from the waves, one of the most challenging problems is the optimisation of motion constraint of the device. Many control strategies have been proposed, including latching [1] and various adaptive tuning methods [2, 3]. A review and discussion of control strategies can be found in [4]. In order to evaluate, compare and implement such control strategies, they must first be optimised for realistic sea states. This optimisation process can be arduous and must be repeated if the system changes - for example, if predictions of future waves are made available to the control system, or mechanical constraints on the motion are changed.

Whereas most optimisation approaches applied to WEC control have relied on describing the system in a simplified form (such as a point absorber), this paper presents a generic optimisation approach that can be interfaced with any model regardless of the complexity. This approach is based on the use of Evolutionary Algorithms (EAs). The practical utility of the approach is illustrated for three different control problems, all applied to a simulation model of a surging WEC. These are 'slow tuning' control [2], latching control [1], and fast tuning by varying damping. The primary aim of the EA approach is to optimise the chosen strategy for realistic sea states (i.e. made up of multiple frequencies) without making prior assumptions about the system.

In this regard, one (rather unrealistic) assumption sometimes made when developing control systems for WECs, is that optima derived for monochromatic seas will also perform well in real seas. To investigate this assumption, two sets of results are presented for each of the control strategies considered in the paper, i.e. these are optimised for (i) simple monochromatic seas and (ii) the Pierson Moskowitz (PM) spectra [5] (defined by T_e, the energy period).

Linear wave theory holds for waves where the height is small compared to the length. In this case, waves can be superimposed, thus the PM spectrum can be constructed by summing monochromatic waves of various periods and amplitudes of random phase. Indeed, the term 'linear waves' refers explicitly to waves for which this assumption holds true. A comprehensive review of the characteristics of sea spectra can be found in [5].

As discussed in section 2, the paper considers a simulation model of a surging plate with dimensions 20 meters side square and thickness 5 meters. Section 3 describes two EAs developed for the optimisation process. Section 4 presents results for a "slow tuning" strategy applied to both monochromatic and mixed waves. In section 5, equivalent results are presented for latching of a device with static damping and spring force. Section 6 presents results for a possible 'fast tuning' approach. Section 7 discusses methods that could be used to apply EAs to machine learning. In the final section 8, conclusions are presented.

2 Model

To evaluate dynamic (time varying) control systems (such as latching and fast tuning) in real seas, a time domain model of the WEC is required. Although evolutionary algorithms are known to be an efficient method for optimising within an extensive search space, a large number of evaluations of the model are necessary. For this reason a recently developed, computationally efficient WEC model is selected for the research [3, 6]. It is based on the equations of motion of a simple mass-spring-damper system, initially considered in the frequency domain. The coefficients of the equation represent the effect of water on the device, as shown below:

$$\{-\omega^2[\mathbf{M}+\mathbf{A}_\omega]+\mathbf{i}\omega\mathbf{B}_\omega+\mathbf{C}\}\xi_\omega=\mathbf{F}_\omega \tag{1}$$

Here, the 'added mass' ($\mathbf{A}_\omega$) refers to the mass of water that moves with the device. Radiation damping ($\mathbf{B}_\omega$) represents the energy transmitted in waves radiating from a moving object in still water. Hydrodynamic spring force ($\mathbf{C}$) refers to the buoyancy of a floating device, whilst the wave force ($\mathbf{F}_\omega$) is the force exerted by a wave on a stationary object. The hydrodynamic coefficients are derived by a computational fluid dynamics package [7]. This package uses panel methods and potential flow theory to calculate the response of offshore structures to linear monochromatic waves.

The model is subsequently converted into the time domain by fitting a system of differential equations with constant coefficients [8]. Due to the construction of the model, the transfer function for the wave force is non-causal and thus unstable. To solve this problem, the transfer function must be partitioned into stable and unstable components. The unstable transfer function is time scaled by -1 and applied to the model in reverse time.

In addition to the forces described by Eqn. 1 the following three forces are introduced into the final model:

- Applied damping (F_B): linear damping force applied by the power take off (PTO) system (Eqn. 2).
- Applied stiffness (F_C): linear additional applied spring force used to tune the device (Eqn. 3).
- Latching (F_L): an extreme damping force that can be applied or removed according to the binary value S_L (Eqn. 4).

$$F_B = B\times\dot{\mathbf{X}} \tag{2}$$

$$F_C = C\times\mathbf{X} \tag{3}$$

$$F_L = \begin{cases} 10^{10}\times\dot{\mathbf{X}} & S_L=1 \\ 0 & S_L=0 \end{cases} \tag{4}$$

More detailed explanations of the complete model are given by references [3, 6]. For the preliminary research described below, the model was initially confined to one degree of freedom, i.e. the surge or movement in a horizontal direction parallel to the direction of travel of the waves. The device modelled for this research is a simple surging plate with dimensions of 20m by 20m by 5m. Finally, the dry mass is chosen to ensure that the device is neutrally buoyant.

This model outputs time series of forces applied $F_A = F_B + F_C + F_L$, and collector velocity $\dot{\mathbf{X}}$. The power capture is then calculated as:

$$\bar{P} = \frac{dt}{T_{rep}} \sum_{t=0}^{T_{rep}} F_{A(t)} \times \dot{\mathbf{X}}_{(t)}$$

where dt is the simulation timestep and T_{rep} is the repeating time of the waves. As all simulations are run to steady state any energy gained or lost as a result of the time varying spring force sums to 0, and as the velocity when $S_l = 1$ is so close to zero no power is extracted. The power is only captured by the damping.

For ease of comparison, all the results for power capture are converted to the capture width ratio (CWR). The power carried by waves is usually represented as power per unit wave crest. The capture width of a device can, therefore, be conveniently represented as the length of wave crest captured in the current sea state ($\bar{p}_{wave}$). To convert this figure into a non-dimensional value, it is subsequently divided by the width of the device (w):

$$\text{CWR} = \frac{\bar{P}}{w \times \bar{p}_{wave}}$$

Therefore, a device with a CWR of 1 captures all of the energy that acts directly on it. However, because of the infinite wave field used in the model, coupled with the interactions between the radiated waves and the incoming waves, the theoretical maximum capture width is greater than one. In fact, the maximum capture width for a small axicymetric collector can be shown to be:

$$CW = \frac{\lambda}{\pi} \tag{5}$$

in surge [9]. It is clear that the associated CWR will increase with wavelength (or period) of the wave λ. Finally, note that since the model is linear (i.e. the assumption of superposition holds), the wave height will not affect the CWR and so is not required for the analysis.

3 Evolutionary Algorithm

Evolutionary algorithms are an example of a parallel meta-heuristic search technique inspired by natural evolution. Unlike many optimisation methods, EAs work from a population of solutions. Recombination operators are applied to share information, and mutation operators to explore new regions of the search space. This allows for complex, epistatic (non-linear) and multi-modal (multiple optima and/or sub-optima) optimisation problems to be efficiently explored [10]. Real-coded EAs (RCEA) are used in a wide range of scientific applications and their characteristics are well understood. They are well suited to performing optimisations in problems with a high dimensionality.

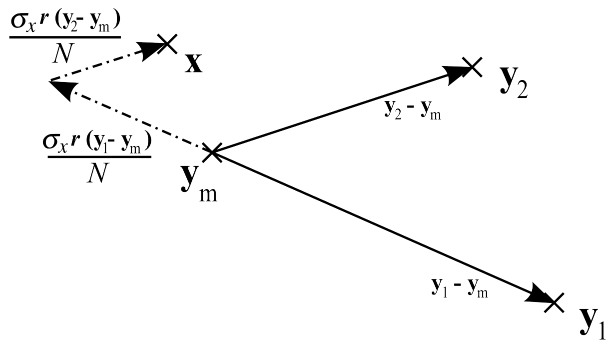
RCEAs are distinct from genetic algorithms in that they manipulate the parameters numerically rather than encoding them as binary information. EAs can be applied to any problem where a decision vector (a vector of parameters that can be chosen, such as the damping and spring coefficients in the slow tuning example below) can be mapped to a solution vector (vector of characteristics to be optimised). The length (N) of the decision vector defines the dimensionality of the search space. Problems with multiple solutions (such as to maximise power capture whilst minimising the power fluctuation) are referred to as Pareto or multi-objective optimisation problems, and rather than producing one optimum, a Pareto set of non dominated optima (solutions vectors where no one characteristic can be further optimised without detrimental effect on the other characteristics) is produced [11]. In the present paper, only one solution is to be optimised (the Capture Width Ratio as described above). However, the method has been extended to the problem of maximising power captured by the device whilst minimising power fluctuation, thus reducing the requirement for short term energy storage (this will be presented in later publications).

For the WEC control optimisation problems considered in the present paper (which are potentially highly multi-modal and epistatic) a RCEA has been selected based on [12]. Two versions of this EA have been applied. First a simple EA has been applied to the slow tuning problem. Subsequently, a more advanced 'Spartan Evolutionary Algorithm' has been developed for the more complex problems of latching and fast tuning. This EA has then been used to train an artificial neural network (ANN) to allow complex control methods. The method used for this training is described below.

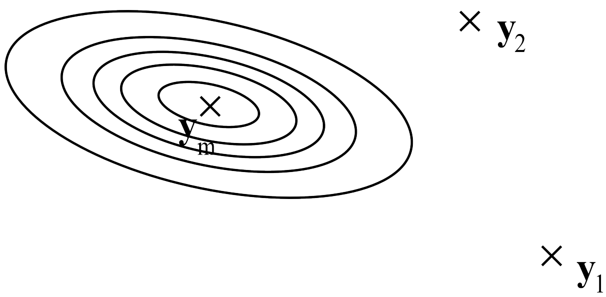
3.1 The Simple Evolutionary Algorithm

Numerous EAs have been proposed in the literature, many of which attempt to produce an optimum recombination operator. For this problem, a recombination operator based on the parent-centric crossover (PCX) operator [12] has been selected (the terms 'crossover' and 'recombination' are equivalent). This operator produces offspring within a Gaussian distribution centred at a parent (the mother), with a standard deviation derived from the spread of the other parents. No mutation operator is required since the recombination operator is able to search any area in the search space. A modified recombination operator developed by the present authors allows for the dimensions of the search domain to take different magnitudes. Hence, if one dimension takes the range $0 \le x_1 \le 1$ and a second is in the range $0 \le x_2 \le 10,000$, then using the new approach [13], the large range of x_2 will not yield erratic results for x_1. Population management is carried out by the Generalised Generation Gap (G3) model also proposed by [12].

The modified PCX operator generates an offspring according to the following equations (see Fig. 1a):



(a) Diagram of the operation of the modified PCX Recombination Operator



(b) Probability distribution resulting from modified PCX

Figure 1: The modified PCX Operator

$$
\begin{aligned}
\mathbf{x} &= \mathbf{y}_m + \sigma_x \mathbf{v} \qquad (6)\\
\mathbf{v} &= \frac{1}{N}\sum_{n=1}^{N} r(\mathbf{y}_n - \mathbf{y}_m) \qquad (7)
\end{aligned}
$$

where $\mathbf{x}$ is the decision vector of the offspring, $\mathbf{y}_m$ is the decision vector of the mother, and $\mathbf{y}_n$ is the decision vector of the n^{th} parent (the number of parents used is set to the number of dimensions of the decision vector). r is a Gaussian random number with mean of 0 and standard deviation of 1. σ_x is a control parameter to be set by the user to set the search pressure. $\sigma_x = 0.3$ has been used in this work. This results in the offspring being produced within a Gaussian distribution in N dimensions around the mother (see Fig. 1b).

A population size of 100 was used. For each generation, 8 offspring are generated from $n+1$ parents, where n is the number of dimensions of the search space. Of a sub population formed by the 8 offspring, the two best members are inserted into the population to replace the two worst members.

3.2 The Spartan Evolutionary Algorithm

On analysis of the performance of the simple evolutionary algorithms on preliminary latching problems [14], it was observed that the EA was having substantial difficulty with the discontinuous nature of the problem. The EA would produce an individual in a poor location of the search, resulting in a poor value for CWR. As this individual was so poor, this information would not enter the population. As a result, this location of the search space would be repeatedly re-searched in successive generations. This was the motivation for developing the Spartan Evolutionary Algorithm [13]. This algorithm introduces a new operator (the Spartan operator) to allow poorly performing members of the population to guide the search by reducing the probability of offspring being produced close to them. As this EA makes use of poorly performing individuals in the population, unlike other EAs, these individuals cannot simply be discarded to maintain the population size. Thus a new population management method has been developed to complement the Spartan Operator. Although this EA was conceived for evolving control systems, it has also been successfully applied to other optimisation problems such as optimising the interaction structure of klystrons [15], which share the problems of a discontinuous search space and large variation in the range of the decision vectors.

In this EA, tournament selection [16] with tournaments of 8 were used. A large selective pressure was required as the population contains individuals that have poor solution vectors.

3.2.1 The Spartan Operator

The Spartan operator operates by allowing poorly performing members of the population to 'kill' offspring before they are evaluated[1]. The overall reproduction process for the Spartan recombination can be described as:

1. Select Parents (stochastic, with preference given to good members of the population)
2. Select Mother (stochastic, with preference given to good members of the population)
3. Generate Offspring using PCX
4. Select Spartans (stochastic, with preference given to poor members of the population)
5. Perform Spartan Operator on each Spartan
6. If the offspring has been killed, goto 4
7. End

The Spartan operator itself operates by generating one offspring from each of the selected Spartans according to the following equation

$$\mathbf{x}_s = \mathbf{y}_s + \sigma_\mathbf{s} \mathbf{v}$$

where σ_s is a control variable set by the user and $\mathbf{v}$ is taken from Eqn. 7. The vector from the spartan to the offspring ($\mathbf{v}_{sx} = \mathbf{x} - \mathbf{y}_s$) is then split into two components, one parallel to and one perpendicular to $\mathbf{v}$. ($\mathbf{v}_{sx\parallel}$ and $\mathbf{v}_{sx\perp}$ respectively). If $|\sigma_s \mathbf{v}| > |\mathbf{v}_{sx}|$ (where $|\mathbf{x}|$ denotes the magnitude of $\mathbf{x}$) then the offspring is deemed to have been killed, and a new offspring must be generated from the parents. This modifies the probability distribution produced by the simple EA (Fig. 1b) by 'pushing' it away

[1]In the ancient Greek city-state of Sparta the Elders would order the death of any infant judged too sickly or deformed to contribute to society. This saved the considerable investment by the state to raise the citizen[17].

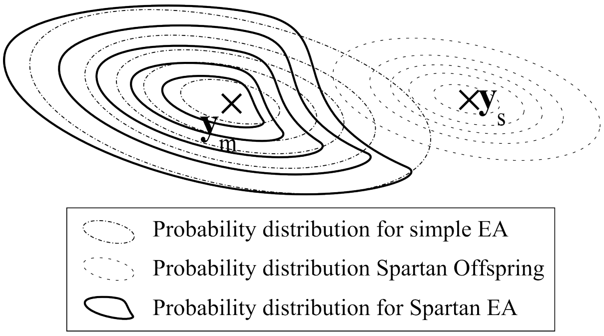


Figure 2: Probability distribution produced by the Spartan recombination operator

from the Spartan. This results in the probability distribution shown in Fig. 2. As this operator is performed before the offspring is evaluated, we negate the time that would otherwise be required to run a simulation.

3.2.2 Population model

Unlike previous EAs where the criteria for maintaining an individual in the population was a function of that individuals fitness, this EA requires us to keep individuals regardless of their fitness if they can be used to guide the search. In order to achieve this we require some method of estimating the probability that an individual will be useful in the future. We assume that if an individual has recently been used (as a parent, mother, or as a spartan that has successfully killed an offspring) then that individual may be of use in the future. Thus we control the population as follows:

Each individual is assigned a 'Significance Index' (s_i). This value is set to 0 on the creation of the individual. s_i is then incremented each generation. If s_i exceeds a maximum value ($s_i > s_{i:Max}$) then that individual is removed from the population.

All individuals now have a finite lifespan. We now require the useful members of the population to be maintained for a longer period. To achieve this we divide an individual's s_i value by 2 if it is deemed to have guided the search by:

- being selected as a mother
- being selected as a parent
- killing an individual as a spartan (individuals selected as Spartans that are unsuccessfull in killing are not deemed to have guided the search).

Spartans were selected using tournament selection with tournaments of size 4 (where the worst individual won). In this work 40 Spartans were used per offspring. This resulted in a stable population size of between 80 and 150. The population size varies depending on the complexity of the problem. In multi-modal or discontinuous problems (where good and bad solutions are located relatively close in the decision space), Spartans are more likely to be successful in killing, thus the population would increase.

3.3 Using Evolutionary Algorithms on Artificial Neural Networks

Artificial Neural Networks are a generic function approximator. It has been shown that an simple feed-forward ANN with sufficient neurons can approximate any function [18]. In the past, the application of ANNs to WEC Control has been difficult, as the primary method for training ANNs is back propagation. This method relies on gradient information being available (the output error must be calculable). This has limited the use of ANNs to problems where the optimisation can be carried out using a different method, and the ANN is then trained to match this optimum such as [19], or where the ANN was used as a constituent of the controller such as a model [20].

In the method used here, the controller is implemented using a simple feed-forward ANN using radial bias neurons. The authors are presently developing an approach based on a recurrent ANN (i.e. with an internal feedback layer), allowing for any classical controller to be evolved, including those based on auto–regression equations. The internal weights and biases are optimised by the EA. Rather than attempting to simultaneously optimise all the required neurons in the hidden layer a cascade training method was used. The ANN was first run with only one hidden neuron. Neurons where then added and the training EA was re-run, thus allowing the ANN to achieve increasing levels of complexity. This was found to give superior convergence. At each stage an initial population size of 80 was used and 120 generations where run.

4 Results for "Slow Tuning"

In the present section the above Simple EA and model are first used to optimise the external spring force and damping force required for maximum power capture in monochromatic waves. Figures 3 and 4 illustrate the optimised forces for a range of wave periods, whilst Fig. 5 shows the associated CWR. These results are compared with the theoretical optimum values obtained analytically from linear wave theory for the same range of wave periods T (seconds) on the same device, and for a point absorber in serge (from Eqn. 5). It is clear that the EA has successfully found the optimum in each case. The EA optima exceed the theoretical optima as these theoretical optima are based the solutions to the second order differential equation describing a point absorber. The system modelled as a finite width, and thus requires modified damping and spring coefficients. The point absorber limit is also exceeded as a result of the finite width of the device.

Having shown that the EA can successfully find the optima in the simple monochromatic problem, it is subsequently used to find the optima for PM spectra of various energy periods (T_e), with the results illustrated in Figures 6, 7 and 8. The proposed optimisation approach yields a smooth curve for each variable, suggesting that the EA has successfully converged to a solution for each

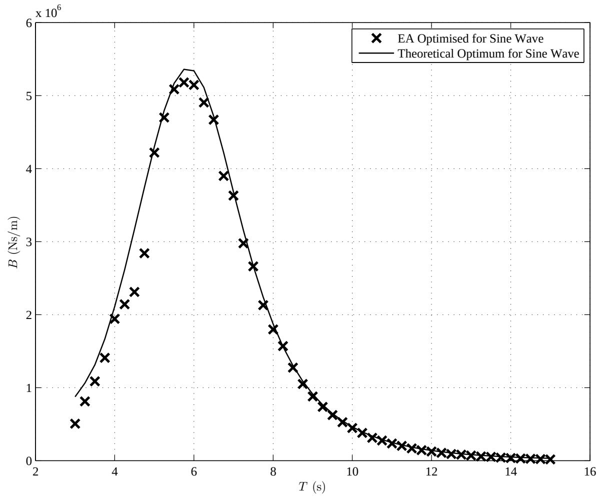


Figure 3: Optimised damping coefficient for slow tuning in regular waves.

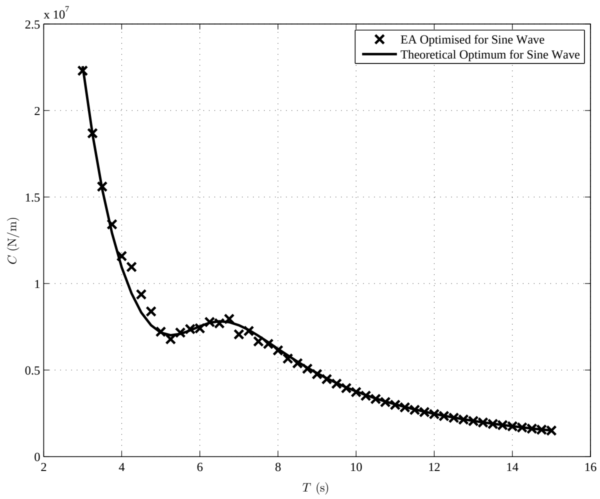


Figure 4: Optimised spring coefficient for slow tuning in regular waves.

wave period considered.

The theoretical optima associated with monochromatic seas is also shown for reference. One interesting feature of these results is the difference in the damping (Fig. 7) and spring (Fig. 8) coefficients, between the optimised results for waves based on the PM spectra (points) and the monochromatic wave equivalents (solid trace). In this regard, a common assumption made in the optimisation of WECs is that monochromatic wave optimisation results can be applied (with some modification) to real waves. However, these results show that the optimisation for monochromatic and real waves will often produce very different results, with no simple relationship between them. The latter observation illustrates the power of the proposed EA approach, which does not require a priori assumptions (except for those used to develop the model).

To further investigate this aspect of the research, Fig. 9 shows the monochromatic wave period to which the device has been tuned (labelled 'T Tuned To') again plotted against the energy period (T_e) of the PM spectra.

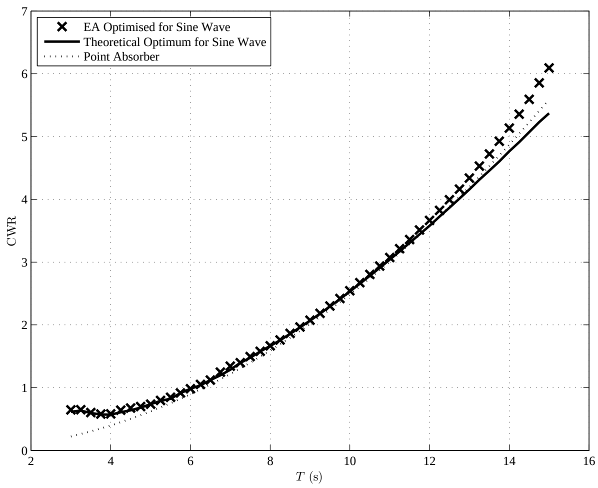


Figure 5: Optimised CWR for slow tuning in regular waves.

The wave period is found using Eqn. 8 below,

$$\omega = \sqrt{\frac{k}{M_t}} \tag{8}$$

Here ω is the device angular frequency associated with the period 'T Tuned To' in Fig. 9, M_t is the total mass of the device $(M + \mathbf{A}_\omega)$ (kg) and k is the applied spring coefficient (N/m) obtained using the EA. The conventional assumption of monochromatic seas yields a linear relationship through the origin, whilst Fig. 9 shows that this is not the case in practise.

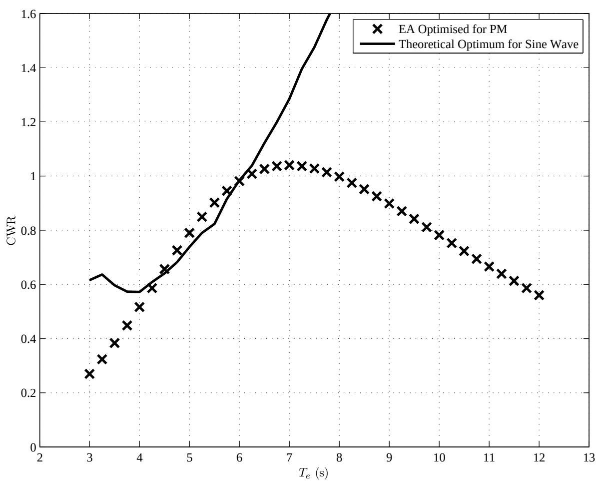


Figure 6: Optimised CWR for slow tuning in PM spectra.

5 Results for Latching

This section considers a more complex control strategy. In particular, latching control is chosen since it is so well known in the field and documented in papers such as reference [1]. Here a brake or latch is applied to the device when the velocity is zero and released when the time to the next wave will (in principle) allow for optimum power extraction.

This controller was generated using an ANN. The cascade learning method was used, resulting in a total

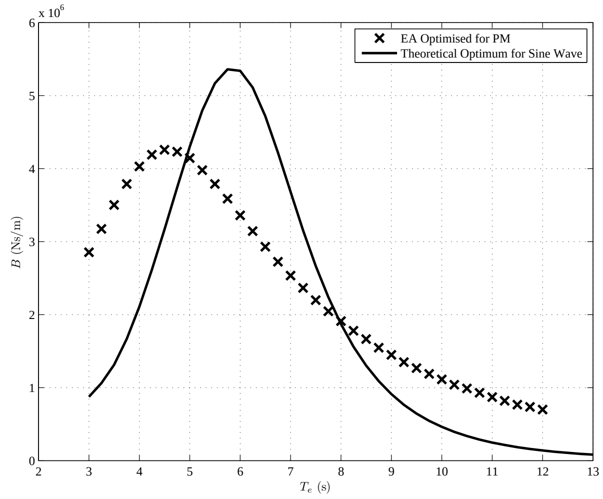


Figure 7: Optimised damping coefficient for slow tuning in PM spectra.

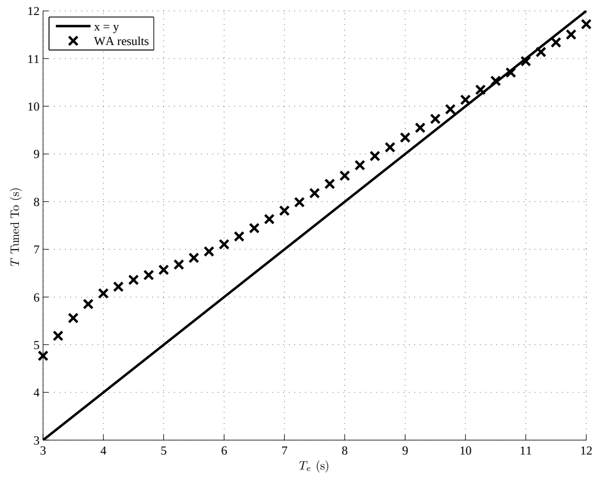


Figure 9: Equivalent regular wave period based on the EA optimisation results for PM spectra (points) compared with the assumed linear solution (solid trace).

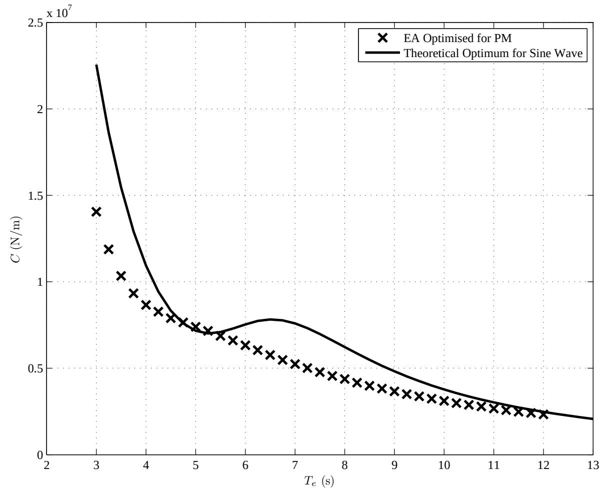


Figure 8: Optimised spring coefficient for slow tuning in PM spectra.

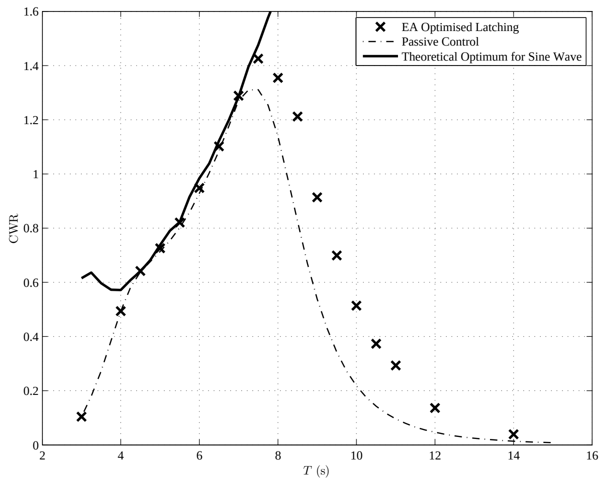


Figure 10: Optimised CWR for latching and passive control in regular waves.

of 3 neurons. The latch was applied whenever the velocity of the device was zero. If the ANN output is unity the latch is released. Only the time to the next wave peak and next wave trough where presented as inputs (in the present research the requirement for a wave estimator is removed by allowing only information available at present to be used, however in this work, the wave estimations are provided externally). With 2 inputs and 3 neurons this approach yields 9 weights and 4 biases, hence a 13-dimensional search space.

The damping coefficient was restricted to 3.4 MNs/m and the spring coefficient to 8.5 MN/m. These values are not optimum for any given frequency; in fact, the device will oscillate at a higher frequency than some of the waves (a standard requirement of latching control). The results for monochromatic seas are illustrated by Fig. 10 which shows that, as the period of the wave increases the latching control is able to substantially improve the performance of the device in comparison to a passive controller (obtained using a constant value for both the spring and damper). This method however, is not able to compete with correct slow tuning at higher periods.

Next, the EA was set the task of optimising the latching controller for PM spectra, again based on a range of T_e values. The results are illustrated in Fig. 11. In this case latching offers only small gains over passive control. One reason for this result is that only the time to the next peak or trough was made available to the ANN, whereas ideally the controller would also account for the current position of the device and the height of the next wave. Such information would allow the controller to 'reject' (i.e. not un-latch for) small waves if it would be advantageous to wait for the next large wave. The authors are presently investigating these issues further and the results will be reported in future publications.

6 Results for "Fast Tuning"

Several methods have been proposed for fast tuning of devices (adaptively altering the damping and/or spring forces on a wave by wave basis). One variant of fast tuning is to vary only the damping applied by the power take off (PTO) between a maximum and minimum limit.

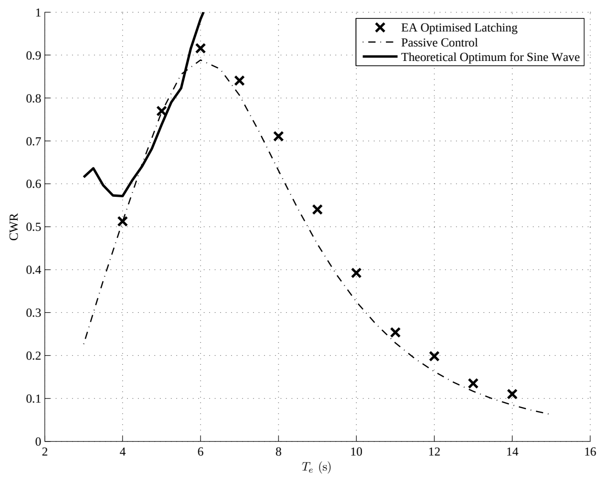


Figure 11: Optimised CWR for latching and passive control in PM spectra

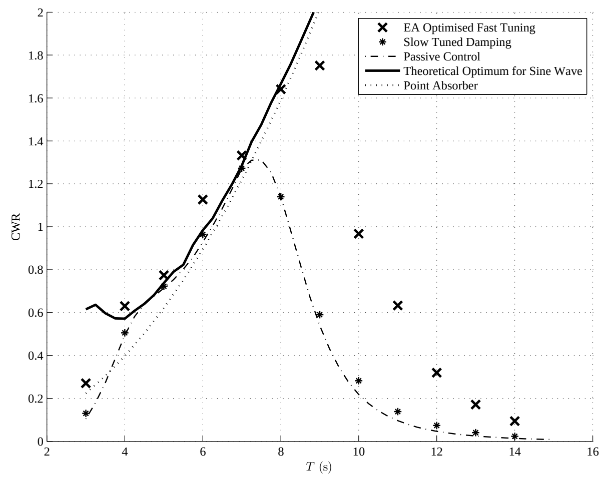


Figure 12: Optimised CWR for fast tuning, slow tuning of damping and passive control in sine waves

This variant is of particular interest to device developers as it can be achieved with existing hydraulic components. For this method the EA was set the task of calculating the instantaneous damping coefficient that would maximise the overall power capture. This damping value could then be used as a set point for a low level control system such as that proposed in [21].

For this set of results the damping coefficient was set to be greater than zero. No other constraints where applied. To allow comparison with the results for latching the same spring coefficient (8.5MN/m) was used and the same inputs were made available. As the required function for damping is more complex than that for latching, more neurons were made available. Neurons were added and the EA continued training until the output from the simulation ceased to improve. Fig. 12 shows the optimised CWR. By comparing these results to Fig. 10 for latching we can see that the fast tuning control is substantially superior to latching in power capture. The CWR is also better than the "Theoretical Optimum for Sine Waves" (obtained assuming static damping and string coefficients) at some frequencies. Again this improvement is a result of the finite width of the device resulting in a higher than second order system (as is assumed for a point absorber). Thus static damping is nolonger optimum. Also shown on this graph is the CWR for slow tuning if only the damping value (B) is chosen. This was also obtained by the EA. Fig. 13 shows the damping coefficient (both fast and slow tuned) and wave elevation for one period in each frequency. It is interesting to note that, although the controller tracks both the peak and trough of the wave for most frequencies, this pattern is not seen in $T = 5$. Further investigation is required to determine whether this is because the EA has found a local optima, or whether at this frequency with this device, the optima does in fact take this form. By referring to Fig. 12 we see that the point for $T = 5$ is lower than we might expect, but is still above the passives or slow tuned control strategies. In the graph for $T = 7$, the damping seems to vary with $|\frac{d\xi}{dt}|$. This may be because the device is approaching resonance (as seen from the

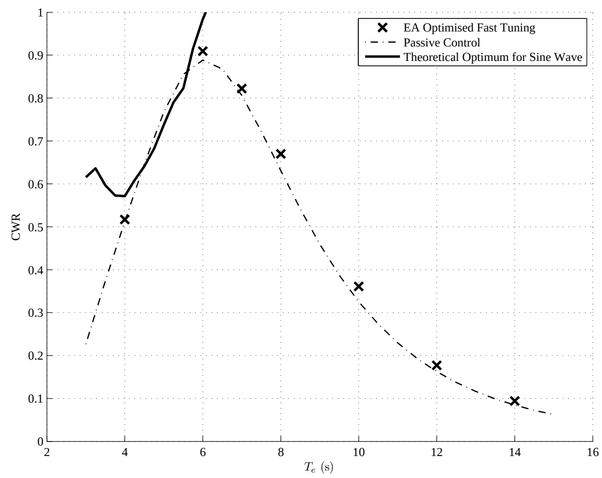


Figure 14: Optimised CWR for fast tuning and passive control in PM spectra

graph for passive control in Fig. 12), thus the forces are in phase with the wave velocity. Interestingly, $T = 7$ is no longer the maximum CWR as the variable damping seems to have pushed the peek CWR to a higher period.

Finally we present the results for fast tuning in PM spectra. These results are similar to those obtained for latching, probably for the same reasons. Again we conclude that more control inputs are required to produce optima for this problem.

7 Machine Learning

One of the most obvious problems with optimisation based on mathematical models is that any inaccuracy of the model will have detrimental effects on the controller when it is applied to a real WEC. In this regard one potential advantage of EAs is their extension to machine learning. With some alterations the EA could be used for an initial model-based optimisation step, until such a time as a reasonable controller has been found. The EA would subsequently be applied to the real device allowing the controller to continue to develop on-line and so helping to overcome the inaccuracy of the model. Such

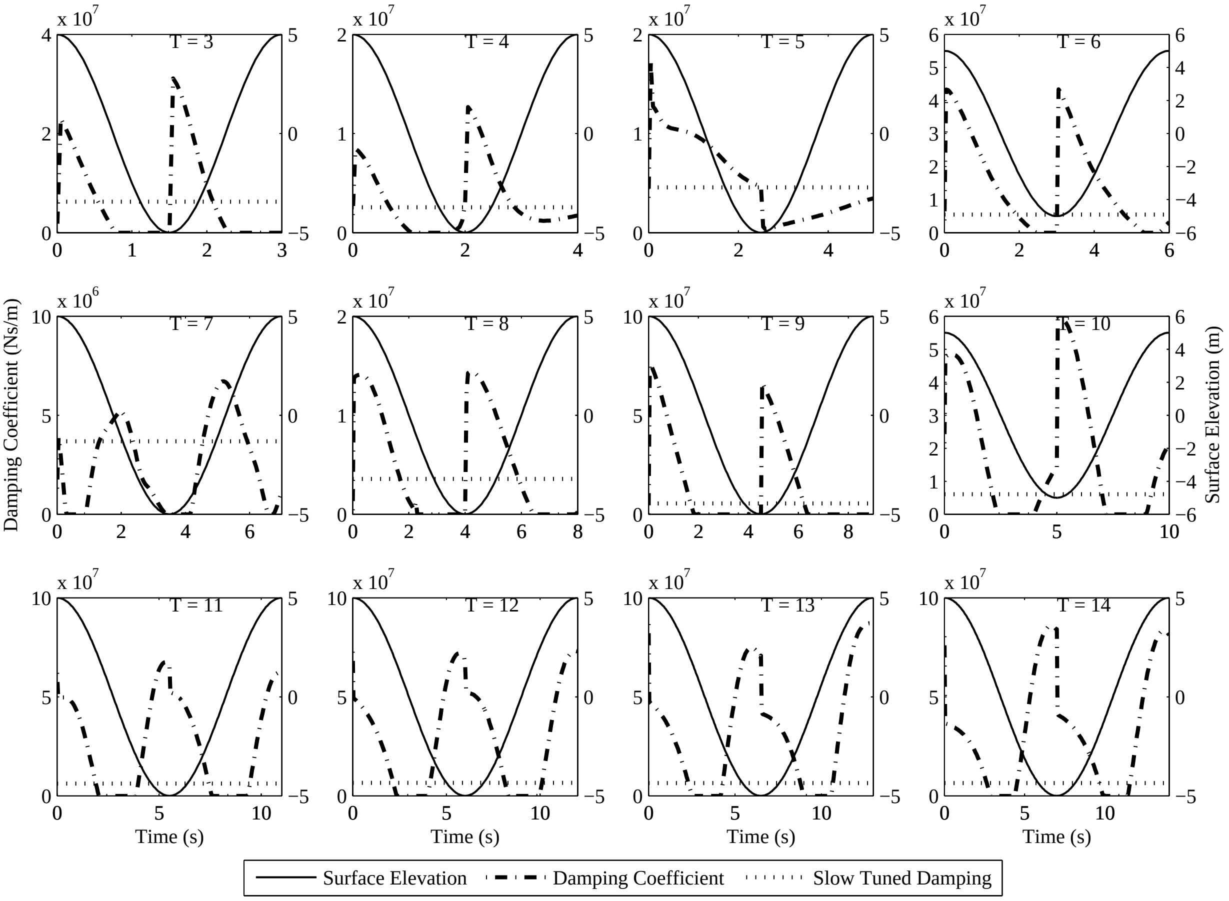


Figure 13: Optimised damping coefficient using fast tuning and slow tuning of damping, and surface elevation for sine waves of different periods (the period is ladelled at the top of each graph).

an approach is presently being investigated by the authors.

A second application of machine learning that could be applied to the EAs is 'slow tuning' of the 'fast tuning' parameters. By ensuring that the EA maintains some small diversity, as the sea state changes, the device would be able to adapt the parameters used in the fast tuning (or latching) controller to maintain maximum power capture.

A final advantage of this method can be obtained with the combination of the above methods. On creating a modified (but similar) design of WEC, or on re-locating the WEC to a new location (with a different sea-state), the EA could be used to modify an existing controller to the new location in the same way that it was used to modify a model generated controller for real conditions.

8 Conclusions

This paper develops a generic approach for WEC optimisation based on the use of EAs. A new EA more capable of solving the problem of WEC control has been developed and demonstrated. Simulation results are presented for tuning an illustrative device in both sinusoidal and Pierson Moskowitz spectra waves and for optimisation of 'slow tuning', 'latching' and 'fast tuning' control systems. The EA was able to find optima for all the problems presented, despite the very large search domain required for the latching and fast tuning control problem. In fact, the proposed EA successfully optimises these control algorithms for realistic seas without prior assumptions. The use of EAs to machine learning in WECs has been discussed and several applications where this could improve performance have been identified.

Further work is required to refine the EA and model in order to improve the efficiency and robustness of the search. This applies particularly as the search domain expands further when considering more complex control strategies, such as state dependent modelling and control [21].

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