

Control techniques for ocean energy applications

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1 Introduction

Control systems, despite often being ‘invisibly’ incorporated within products, devices and vehicles, are ubiquitous. They are prevalent within the automotive and aerospace industries and form part of the vanguard of technologies in increasing performance, improving fuel economy and increasing safety. One of the most appealing aspects of incorporating control technology in many systems is that the addition of extra control functionality can usually be achieved merely through the addition of extra software code though, in many cases, additional sensors and actuators may be required.

This relatively simple implementation modality masks both the capability of control systems and the high level of engineering underpinning the development of a suitable control algorithm. For example, many high-performance model-based control design methods require an accurate mathematical model of the system to be controlled and a significant number of man-hours can be absorbed in modelling. Nevertheless, there is usually a good case to be made for the incorporation of control technology to improve the performance (both technical and economic), reliability and safety of a system. In this chapter, we will examine the role that control engineering can play in making ocean energy technology more competitive.

In an ideal world, one should consider the design of a complete system from the top down. However, convention has it that physical systems are usually designed by the discipline-specific experts and the control problem is then addressed in a subsequent step by control engineers, working in collaboration with the discipline-specific experts. Such an approach, though prevalent in the bulk of industrial applications of control, is non-optimal. There are some notable exceptions, though, with a notable one being in the design of flight control systems. In the 1970’s, aircraft were designed to be open-loop unstable with the

result that, in the absence of a closed-loop control system, such aircraft could not be flown by human pilots. While this put complete reliance on the control system, the advantage was that significant gains in aircraft manoeuvrability and economy of flight could be achieved. Some preliminary studies [23] have been carried out which examine the interaction between the optimal design (geometry) of a wave energy device and an accompanying control system. The results suggest a strong interaction between the type of control system used and the optimal device geometry, with optimal energy capture as an objective.

For ocean energy applications, control systems can offer performance benefits. Assuming that the prime energy converter is designed first, the addition of control can offer significant energy capture enhancement. While the area of tidal turbine control is not so well established, there are close similarities with wind turbine control, one notable difference being that the density of the medium is about 1000 times greater in the case of tidal turbines. A general study on wind turbine control [50] suggests that a variable-speed turbine, requiring torque and speed control, can absorb 2.3% more energy than a fixed-speed counterpart, where the speed is fixed by the electrical grid frequency. In the case of wave energy, the numbers are more dramatic. A study on latching control [4], which is a relatively simple implementation of the more ideal complex-conjugate control, suggests that energy capture can increase by as much as a *factor* of 2 with control in irregular waves and by up to a *factor* of 4 in regular waves.

We also need to consider if the addition of a control system may drive the system more aggressively in an attempt to increase energy capture, perhaps leading to shortened device lifetimes. While the addition of control to a (tidal) turbine is likely to be relatively benign, the use of motion-exaggerating control for a reciprocating wave energy device can have a dramatic effect on device motion. Consequently, the balance between increased energy capture (income) and increased device wear (cost) needs to be carefully considered. Some formulations are now appearing which attempt to balance such quantities [11], though explicit enumeration of the cost of increased wear remains an open issue.

While potentially effecting more aggressive device motion, there are some redeeming features of control which may help the designer in practical application. For example, physical constraints can be explicitly included in many control formulations [24], resulting in a control action that respects (and is optimal within) the physical system constraints. In addition, most optimal control formulations allow some explicit trade-off between control action and the main objective (e.g. setpoint tracking, energy maximisation, etc), which provides a design handle on the level of aggressiveness of the control [37]. Control science also provides a body of knowledge relating to the design of control systems which are tolerant (in some respect, but usually with reduced performance) to device, actuator or sensor failure [47].

Finally, one might consider the various ‘levels’ of control that might be required in an ocean energy application. Clearly, there is a top level of supervisory control which assesses the incident energy resource and may curtail the operation of the device in the face of extreme conditions. Such curtailment may be requirement in order to preserve the device integrity, ensure safe operation, or be required by legislation, as in the case of wind turbines. For the tidal energy case (unlike wind energy), the extremes of current flow are known and the tidal current device will be designed to operate in energy capture model over this relatively narrow operating range. Wave energy devices, however, will frequently encounter sea states which are outside their normal operational envelope and some supervisory strategy may be necessary to ensure that device integrity is retained. While such supervisory control is important, it is beyond the scope of this chapter (**or book ?**).

2 What is control ?

While the reader might like to peruse the 1548 page excellent ‘encyclopedia’ of [36] in an effort to understand the essence of control, it is pertinent to try to articulate the fundamental utility of control that makes it useful in the context of ocean energy. In general, control attempts to devise algorithms that force a system to follow a desired path, objective, or behaviour modality. Traditionally, the control problem is defined by a tracking problem, as shown in Fig.1, where the objective is for the system output to follow the reference input. While problems of these type do occur in ocean energy applications, for example speed control of a tidal turbine, it is more useful to broaden the set of problem descriptions and potential solutions a little, in order to assess the potential of control engineering in an ocean energy context.

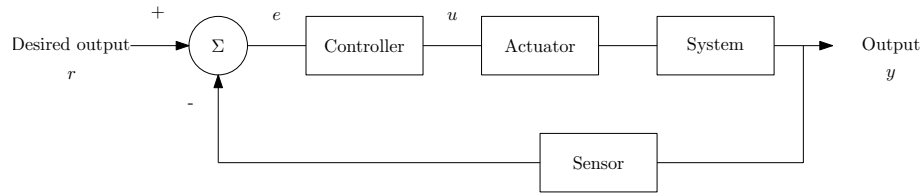


Figure 1: Typical tracking problem for a control system

In general, control problems are usually defined by some subset of the following:

Definition 1: General control problem definition

Maximise/minimise Performance objective (max. energy, min. error)

subject to: System constraints (amplitudes, rates, forces, etc)

i.e. a constrained optimisation problem. The definition above is not inconsistent with the purpose of the system in Fig.1 where the objective function is usually some measure (e.g. a quadratic measure) of the difference between the output and its desired value i.e. the tracking error.

The desired performance of the tracking system in Fig.1 can be specified in a variety of ways:

1. Desired transient response e.g. [32]
2. Desired steady-state response e.g. [52]
3. Desired closed-loop poles (roots of the closed-loop transfer function) e.g. [9]
4. Trade-off between control energy (u^2) and tracking error (e^2) [1]
5. Minimisation of the sensitivity of the closed-loop system to variations in the system description [55]
6. Minimisation of the sensitivity of the closed-loop system to external disturbances [55]

Items 5 and 6 in the list above relate to the system *robustness* and specific control methodologies to address these objectives have been developed since the late 1970s.

In most cases, control design methods provide an explicit solution for the controller in Fig.1, while some methods solve the more general optimisation problem defined above at each time step. In the next section, we will see how such specific or general solutions can be useful in the control of ocean energy devices.

Finally, some control methods require a mathematical model of the system in order to determine the control algorithm and such methods are termed *model-based*. The requirement for an accurate mathematical system model often involves considerably more work than the calculation of the controller itself, though *system identification techniques* [38] can be employed to determine a black-box model i.e. a model which has no structural relationship to the physical system. The combination of system identification techniques with a mathematical procedure for controller determination can be used to develop adaptive controllers, which have the capability to adapt to unknown (in ‘self-tuning mode’) or time-varying systems. Adaptive control schemes based on linear system models also have the capability to track variations in a linear model due to the presence of nonlinearity, though nonlinear systems are best controlled with a dedicated fixed-parameter nonlinear controller. Significant care and attention must also be paid to adaptive schemes to ensure stability and convergence over all operating regimes [45].

For ocean energy systems, the modelling effort can be considerable, since hydrodynamic modelling is involved. While a variety of comprehensive nonlinear modelling methodologies are available for hydrodynamic modelling, including smooth particle hydrodynamics (SPH) or computational fluid dynamics (CFD) approaches, the difficulty of incorporating such models into a control formulation require the use of more compact and structurally simple models. In addition, the very significant computational complexity of SPH or CFD models preclude their direct use for real-time controller implementation. Instead, model-based control strategies usually use compact linear models, which are based on either local linearisation about an operating point (see, for example, [35, 8]) for the turbine case, or linear boundary-element models [13, 15] for the wave energy case. Even modest nonlinear extensions to linear boundary element methods can result in models which are computationally intractable for real-time control [43], while some specific parameterisations (e.g. to include viscosity effects [7]) give nonlinear parametric forms that may be possible to incorporate in model-based control schemes.

2.1 Varieties of control algorithms

With a view to an examination of the spectrum of control methodologies available, the diagram of Fig.1 is now slightly re-configured to that of Fig.2 for convenience of notation. The operators K , G and H are purposely free of continuous-time/discrete-time or linear/nonlinear classification, with the intention of keeping the discussion as broad as possible. It is hoped that any loss of mathematical rigour is compensated by the increased scope of the diagram’s use!

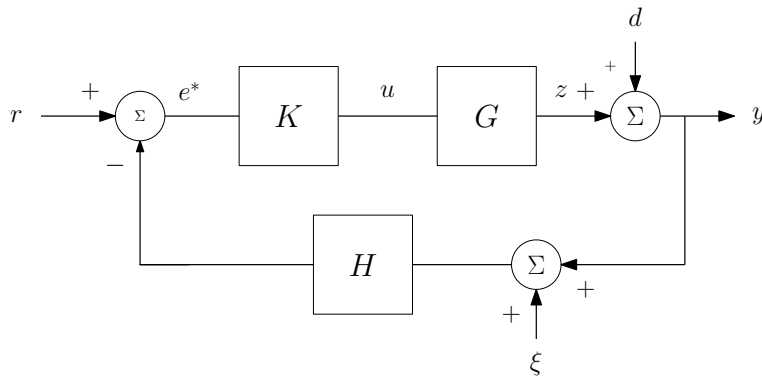


Figure 2: Feedback system specification

In Fig.2, the ‘system’ and ‘actuator’ blocks of Fig.1 have been combined into

G , while the additional inputs, d and ξ , represent disturbances (deterministic and/or stochastic) and measurement noise, respectively. The '*' designation is used to denote that e^* is not necessarily an exact calculation of $e = r - y$, since H may be non-unitary.

2.1.1 PID control

One of the most ubiquitous control methods and has been a mainstay of process control and many other application areas for over 7 decades. In this paradigm, the control signal is formed as a linear combination of error, integral of error (which aids good steady state control) and 1st derivative of error (which aids good transient response), expressed in continuous-time form as:

$$u(t) = k_p e^*(t) + k_i \int e^*(t) dt + k_d de^*(t)/dt \quad (1)$$

Various other forms, including the reduced PI and PD forms, are also possible, while a number of embellishments, including velocity forms, bumpless transfer, derivative on output only and derivative filtering make the PID controller more use in many practical applications. The proportional, integral and derivative gains (k_p , k_i and k_d respectively) can be determined from a variety of model-based design rules, or can be tuned by hand. The strong intuitive relationship between the controller parameters and (particularly) the closed-loop step response gives the opportunity to tune, or fine-tune, the parameters of the PID controller by observing the resulting changes to the closed-loop response and has been largely responsible for the widespread appeal of PID control. A comprehensive treatment of PID tuning rules is given in [48]. PID controllers are best suited to systems with predominantly linear dynamics, though gain-scheduled versions can be used to control non-linear systems [30].

2.1.2 Pole placement

The controller K can also be determined by defining the positions of the desired closed-loop poles, which are strongly related to the closed-loop transient response. Such calculations can be easily done in either discrete- or continuous-time, though transient response specifications are more easily specified in the (continuous-time) s-plane. Designs performed in continuous-time can be easily transformed to discrete-time versions using discretization based on pole-zero mapping [28]. Pole placement required a model of the system, but is easily performed for both models described by transfer functions [3] or in state-space form [18]. For systems described in transfer function form, some design freedom (choice of observer polynomial) is available beyond achievement of the closed-loop poles, while pole placement for multivariable systems (systems with multiple inputs and outputs) normally results in a nonunique solution for the feedback gains, allowing some extra design freedom which can be used to address robustness issues, etc.

2.1.3 Optimal control

There are many varieties of optimal control, which has its origins in the birth of the 'modern control' era of the 1960s. It can be used with both state-space [1] and transfer function [25] models and is equally applicable to continuous- and discrete-time models. Traditionally, the (continuous-time) linear quadratic regulator (LQR) optimal control problem is formulated as:

$$\min_u J = \int_0^{t^*} (e^T Q e + u^T Q u) dt \quad (2)$$

where $e = r - y$ and Q and R are weighting matrices which define the trade-off between error minimisation and reduction of the control energy used. For

example, in high accuracy servomechanism problems, the choice of $Q \gg R$ is usually made, while in satellite control applications, where fuel is limited, a choice of $R \gg Q$ is more appropriate. Since there is an explicit relationship between Q, R and the closed-loop poles, traditional optimal control can be seen as an alternative way of determining the closed-loop poles. The solution to the problem in (2), however is not simple, requiring the solution to a Riccati equation for systems described in state-space form [1] and a Diophantine equation for the transfer function form [25]. However, a range of computer-based tools are now available to assist with the solution to these equations.

In general, the formulation in (2) is for linear models and can be specified either as a finite-horizon (t^* is finite) problem, or as an infinite horizon ($t^* \rightarrow \infty$). A particular evolution of the finite horizon optimal control problem which is formulated in discrete time and uses a future prediction of the system output is model-based predictive control (MPC) [56], which has seen significant adoption in the process, and other, industries, rivalling PID control in popularity.

The basic problem formulation for MPC is:

$$\min_{u(0), \dots, u(h_c)} \sum_{k=0}^{h_p} e(k)^T Q e(k) + \sum_{k=0}^{h_c} \Delta u(k)^T R \Delta u(k) \quad (3)$$

where $\Delta u(k) = u(k) - u(k-1)$, $e(k) = r(k) - y(k)$ and h_p and h_c are the prediction and control horizons, respectively. Using a model of the system, the future output is predicted up to h_p steps ahead and the optimal control sequence, $u(0), \dots, u(h_c)$, calculated so that the system output follows a reference trajectory. The next control input, $u(0)$ is then applied to the system and the optimal future control sequence recalculated. This ‘receding horizon’ procedure allows the system to effectively counteract output disturbances (d in Fig.2) and gives the control paradigm good robustness properties.

MPC is flexible and can deal with a number of practical system characteristics. For example, if the system contains pure delay (of, say, n_d steps) then the performance function in (3) is recast with n_d as the lower limit on the first summation term. This effectively implements a Smith predictor [41], placing the delay component outside the control loop. An extension which is very useful in many applications is the possibility to implement constraints on the system inputs, outputs and states. This can be used to implement an optimal control which respects physical limits on system variables, such as velocities, positions, forces, currents, voltages, etc. The constrained formulation [40] includes (3) together with a set of constraints:

$$\begin{aligned} y_{min} &\leq y &\leq y_{max} \\ u_{min} &\leq u &\leq u_{max} \\ |\Delta u| &\leq u_{max} \end{aligned}$$

etc

MPC can use both linear and nonlinear models. For the basic MPC formulation, an algebraic solution for the $u(k)$ in terms of $y(k)$ and $r(k)$. For MPC formulations involving constraints and/or a nonlinear system model [29], the general (numerical) optimisation problem in Definition 1 above must be solved. However, the subject of efficient optimisation algorithms for constrained/nonlinear MPC has received considerable attention [53].

Finally, one very useful exploitation of the general MPC framework is the possible substitution of the quadratic regulation penalty (e.g. $e^T e$) in (3) with an energy related term, such as **current x voltage** or **force x velocity**, coupled with a change from minimisation to maximisation of the performance function. Such a possibility has particular relevance to ocean energy and will be further discussed in Section 3.

2.1.4 Robust control

Robust control theory developed rapidly from the 1970s as a paradigm that explicitly tried to synthesise controllers which were optimally robust to variations in the system (due to time variance, nonlinearity, etc) and disturbances. For robust control design, both a system model *and* a measure of the uncertainty in the model. The uncertainty can be expressed in both structured (leading to μ -synthesis [49]) or unstructured (leading to H_∞ design [51]) forms. For illustration, the robust control formulation for H_∞ design will be briefly outlined. The performance function for the classical H_∞ control design problem can be specified as:

$$J_\infty = \left\| \begin{array}{c} W_1(s)S(s) \\ W_2(s)T(s) \end{array} \right\|_\infty \quad (4)$$

where

$$S(s) = (1 + GKH(s))^{-1} \quad , \quad T(s) = GKH(s)(1 + GKH(s))^{-1} \quad (5)$$

are the sensitivity and complementary sensitivity functions (with reference to Fig.2) respectively, and we note that $S(s) + T(s) = 1$. $S(s)$ specifies the closed-loop sensitivity to variations in $G(s)$ and $K(s)$ and also is the transfer function relating the disturbance, d , to the system output, y . $T(s)$ specifies the relationship between the measurement noise, ξ , and the output, y and also determines robust stability.

Robust stability is guaranteed by ensuring that the weight $W_2(s)$ overbounds the plant (multiplicative) perturbation in the maximum singular value sense as:

$$\bar{\sigma}[W_2(j\omega)] \geq \bar{\sigma}[\Delta(j\omega)] \forall \omega \geq 0 \quad (6)$$

where:

$$G(s) = G_o(s)(1 + \Delta(s)) \quad (7)$$

with G_o being the nominal system model. In general, the weighting function $W_1(s)$ is chosen to:

- Penalise sensitivity, $S(s)$, at low frequency, giving good low frequency disturbance rejection, and
- Ensure that system performance (dynamic response) is maintained in spite of parameter variations in $G(s)$ at low frequency.

W_2 is chosen to:

- Ensure robust stability by covering $\Delta(s)$ i.e. that condition (6) is met, and
- Attenuate high-frequency measurement noise in ξ , by driving $T(s)$ down at high frequency.

In addition, the relative positions of $W_1(s)$ and $W_2(s)$ determine the closed-loop bandwidth, controlling the dynamic response to setpoints (r) and disturbances (d).

One of the issues with early robust control was that, while robustness was explicitly handled, no specifications on performance (e.g. tracking) could be explicitly made. One solution is to design an LQR regulator and then reinforce controller robustness using the loop transfer recovery (LTR) method [42]. Robust version of predictive control, including the possibility to deal with constraints are also available [33] and H_∞ design methods have also been extended to nonlinear systems [27]. While robust control presents the possibility to deal with nonlinear systems using a linear robust control approach, where the nonlinearity is reflected in the uncertainty in the linear model, this is not a

recommended approach, since the performance will be degraded across the operational spectrum (in order to ensure robust stability), compared to a dedicated nonlinear design.

In general, the optimisation problems resulting from minimisation of cost functions such as (4) are complex, but formulation of robust control problems as a set of linear matrix inequalities (LMIs) allows the application of efficient numerical tools [22].

2.1.5 Nonlinear control

While control algorithms developed for linear systems apply to the vast bulk of such systems (with some exceptions relating to open-loop stability/instability, non-minimum phase zeros, presence of time delay, etc), there is no general theory of nonlinear systems and most nonlinear control design methods are for specific nonlinear forms, e.g. Hammerstein, Volterra, etc. A number of generic nonlinear control formulations, and using artificial neural network (ANN) system models, are presented in [46] and [29] and include methods inspired by model-reference adaptive control, internal-model control (IMC) and MPC. An alternative is to try to apply feedback linearisation [31] to the nonlinear system, followed by linear design. Other popular nonlinear control approaches include backstepping [34] and sliding-mode control [57], which is a form of variable structure control using high gain and a switching control strategy to implement robust feedback control.

3 Control systems for ocean energy

While Section 2 has focussed mainly on the classical control problem of regulation of some variable to a desired value, and indeed such problems are encountered in ocean energy applications, there is a broader set of problems which can also be addressed by control system technology. The purpose of this section is to present this broad problem definition and examine how this problem may be addressed, or broken down into smaller parts which may be more easily solved.

3.1 Problem specification

In the case of both tidal and wave energy, the general problem is to maximise energy capture, subject to grid and environmental constraints. However, we might modify the objective of energy capture maximisation to that of maximisation of economic return [11], which requires a balance to be achieved between maximising energy capture and minimising wear on components. However, the move to an economic performance function also requires the accurate articulation of capital and operational costs, which is quite onerous for the relatively immature field of ocean energy, and significantly complicates the optimisation problem. Instead, for the current analysis, in order to retain a focus on the fundamental control issues, we will limit ourselves to the general problem of energy capture maximisation.

There are two broad approaches which may be taken to solve the energy maximisation problem:

- (a) Overall extremum seeking control [2], with little use of a detailed model of the system, or
- (b) Determination of an optimal setpoint for the system, which gives maximum energy capture, followed by a regulatory to make sure this setpoint is achieved.

Option (a) is attractive from the point of view of the lack of requirement for a detailed model, but may have dynamic performance limitations in convergence

rates and may have difficulty finding a global maximum over a non-convex performance surface. For example, in a wave energy application, the controller may not converge to the appropriate setting before the instantaneous wave frequency changes.

Interestingly, a common framework for both wave and tidal energy may be adopted for option (b), as shown in Fig.3. The particulars for tidal and wave devices are detailed in Sections 3.2 and 3.3. For the standard feedback regulation

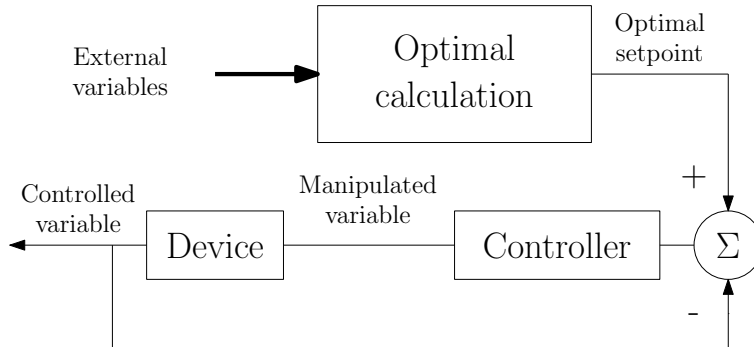


Figure 3: Sequential optimal calculation and regulation

section of Fig.3, any one of the techniques mentioned in Section 2 can be chosen, based on the particular system description, the level of control fidelity required and the appetite for computational complexity. Since both tidal turbine and wave energy device dynamics are relatively slow (with the possible exception of the power converter section), there is much scope for the implementation of complex control strategies.

3.2 Tidal energy

in the case of a tidal turbine, optimal blade pitch, β , and rotor velocity (via the tip/speed ratio, λ) are set based on the incident flow velocity in order to maximise the power coefficient, C_p . Standard feedback loops are then used to control the pitch actuators and the torque in the rotor in order to achieve the desired pitch angle and rotor speed. The manipulated variable for the pitch control is the power to the pitch actuators (voltage and/or current). For torque control, either the back-to-back (B2B) power converter (where one is used) or the generator excitation can be used as control actuators.

It is important to note that the relationship between β , λ and C_p is specific to each tidal turbine and must be determined for each particular case. However, this relationship is then fixed, though some slight variation may occur due to component wear, or possible water density variations. We also note that when a tidal turbine reaches its rated power, the turbine must be ‘depowered’ in order to avoid exceeding any rated specifications. In this situation, it is not required to maximise power conversion and, for variable pitch turbines, blade pitch can be adjusted in order to limit power converted.

Control system for wind turbines are now well developed [35, 8, 50] and many of these schemes can be successfully exploited in tidal turbine control. However, some important differences between wind and tidal turbines are articulated in [14]. **Section XXXX of this chapter examines the detail of control strategies for marine current turbines**

3.3 Wave energy

For the wave energy case, the optimal velocity profile needs to be determined from the excitation force experienced by the device and the power take-off (PTO) system is then manipulated by the feedback controller to achieve this

velocity profile. The optimisation problem in Fig.3, for the wave energy case, is effectively an impedance matching problem, since the input to the system is broadly sinusoidal and the wave energy device can be represented by it's (complex) intrinsic impedance, as represented in Fig.4. For optimum power transfer

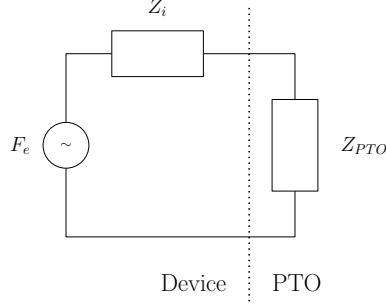


Figure 4: Impedance matching problem for wave energy device

from the device to the PTO, we can use the well-known result:

$$Z_{PTO} = Z_i^* \quad (8)$$

where $()^*$ denotes the complex conjugate. In order to see the typical form of Z_i we can use the simple wave energy device model, originally proposed in [13]:

$$m\ddot{x}(t) + m_\infty\ddot{x}(t) + \int_0^{+\infty} h_r(\tau)\dot{x}(t-\tau)d\tau + K_v\dot{x}(t) + k_b x(t) = f_{ex}(t) \quad (9)$$

where

$$f_{ex}(t) = \int_{-\infty}^t h_e(\tau)\eta(t-\tau)d\tau \quad (10)$$

with $\eta(t)$ being the free surface elevation, $h_e(t)$ and $h_r(t)$ are the kernels associated with the excitation force and radiation damping convolutions, respectively, m is the device mass, m_∞ is infinite frequency component of added mass and K_v and K_b are the coefficients of viscous loss and restoring force (buoyancy/gravity) respectively. With:

$$B(\omega) = \mathcal{F} \left[\int_0^{+\infty} h_r(\tau)\dot{x}(t-\tau)d\tau \right] \quad (11)$$

we can identify the *intrinsic impedance*, Z_i , of the device as:

$$Z_i(\omega) = F_{ex}(\omega)/V(\omega) = B(\omega) + k_v + j\omega \left[m + m_\infty - \frac{k_b}{\omega^2} \right] \quad (12)$$

If the wave excitation is monochromatic, i.e. ω has a single value and is known, then (8) is straightforward to calculate, with the optimal velocity profile:

$$v_{opt} = \int_{-\infty}^t h_v(\tau)f_{ex}(t-\tau)d\tau \quad (13)$$

with $h_v(t) = \mathcal{F}^{-1}\{1/2b(\omega)\}$. However, real (irregular) sea conditions present some difficulties:

- Reactive power must be supplied by the PTO,
- The calculation in (13) is non-causal, and
- There are no constraints on the motion.

With regard to constraints, Budal[17] and Evans [16] considered optimal power absorption under motion constraints. As discussed previously, MPC provides a mechanism to allow motion constraints to be explicitly specified in the control problem formulation. The obvious difficulty with MPC is that it's normally used for quadratic regulation problems (see (3), but reformulation of the cost function to address a suitable energy maximisation problem, as:

$$\min_{u(0), \dots, u(h_c)} T_s \sum_{k=0}^{h_p} [v(k)f_{ex}(k) - v(k)f_r(k)] \quad (14)$$

where available mechanical energy (i.e. the difference between excitation and radiation energy, assuming no losses) is maximised, gives the opportunity of using standard MPC tools. In (3), T_s is the sampling period, noting that power is the product of force and velocity, while energy is the integral (or discrete-time summation) of power over time. Relatively standard MPC formulations for wave-energy device control have been considered in [26] and [12], while an MPC problem which parameterises the system variables in terms of basis functions [6] results in the computationally straightforward solution of a set of linear equations. It would be reasonable to suggest that MPC implicitly implements complex-conjugate control, since the performance function is the same as that for impedance matching, albeit with the optimum obtained within the envelope of constraints. Finally, a particularly simple sub-optimal controller, but with the capability of implementing amplitude constraints, is reported in [21].

With regard to the causality problem, a number of causal approximations to complex conjugate control are available, including latching [10, 4], declutching [5] and other methods, e.g. [39]. One causal approach, which uses the broad LQR strategy of Section 2.1.3, is reported in [54]. An alternative way of dealing with non-causal control is to attempt to predict the future free-surface elevation or the excitation force, as required in (13). While (13) suggests that a forecast of f_{ex} for $t \rightarrow \infty$ is required, [20] evaluates the realistic forecasting requirements in terms of the device and the typical seas in which such a device might operate find that, in general, there is a strong positive correlation between forecasting requirements and likely ease of forecasting. Some forecasting methods for excitation force and free surface elevation are described in [19].

Section XXXX of this chapter examines the detail of control strategies for wave energy devices

4 Conclusions

Control technology, which includes significant components of system identification (black-box modelling) and optimisation, has a significant role to play in increasing the functionality, performance and economic viability of ocean energy systems. While the more traditional control problem of output regulation appears to a significant extent in ocean energy application, some of the primary issues (such as converted energy maximisation) are more difficult to address using standard control methods. However, some control methods which solve more general optimisation problems (as articulated in Definition 1), such as MPC, can be adapted to address the energy maximisation objectives.

Other aspects of control technology which, to date, have not seen application in the ocean energy area include fault-tolerant control [44] which could be important in ocean energy systems which typically have very limited access for maintenance. Fault-tolerant control could also be applied to arrays of devices, in order to maintain grid compliance and smooth energy output of an ocean energy farm if one or more devices develop faults.

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