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# WEC Optimization Tool Scoping Report

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# ABSTRACT

This report details the background, design, and initial results for wave energy converter design optimization tool. This tool is intended to provide researchers and developers with a means of optimizing existing wave energy converter designs by including realistic dynamics and control algorithms early in the design cycle.

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# CONTENTS

# 1. INTRODUCTION

This report provides a summary of the planned development of a tool for performing design optimization of wave energy converters (WECs). The concept for this project was conceived based an initial study that examined the potential to develop standard design class WECs based on distinct regional trends in US wave climates [45, 47]. In this previous effort, a single scaling factor for the Reference Model 3 point absorber [46] was considered in order to investigate the degree to which a finite set of standard design classes for a specific WEC archetype could be achieved to facilitate WEC product line development in the US and device-type certification; resulting in significant savings in design and manufacturing costs. This analysis on WEC scaling was in turn used to infer on the question of classification systems for WECs.

The current effort, which is the focus of this report, extends upon this initial study with the goal of providing a generalized open-source tool for performing WEC design optimization studies by incorporating realistic control dynamics in the process. This report summarizes the general structure of this tool, provides a theoretical basis for the work, discusses the development stages, and shows some initial results.

## 1.1. A PRIMER ON OPTIMIZATION

Computational optimization is the use of automation to systematically improve a design. With foundations in numerical methods, optimization requires the definition of mathematical elements relevant to the problem at hand. Primarily, the optimization approach will select potential new designs; these designs consist of *design variables*, or the parameters that define a design. For example, in the optimization of a cardboard box to fit around a product of a set size while minimizing the amount of cardboard, the design variables are likely the length, width, and height of cardboard used. An optimization algorithm systematically develops potential solutions by changing the values of these design variables and selecting the best values for these design variables to meet design objectives.

In order for an optimization algorithm to be able to improve potential solutions, an *objective function* is required. The objective function (or functions) in an optimization formulation is used to quantitatively establish the relative "goodness," and is generally minimized or maximized. The objective function must be simple enough to enable efficient evaluation, but complex enough to provide accurate results. In our cardboard box example, the objective function is to minimize the total amount of cardboard used; this can be represented in a myriad of ways including by weight, volume, surface area, etc. In the optimization of energy generating technologies, objective functions have typically included minimizing the Levelized Cost of Energy (LCOE), maximizing electricity generation, or maximizing profit. Sometimes it is prudent to explore multiple objective functions concurrently, which is called *mulitobjective optimization*.

Objective functions usually require the intermediate evaluation of *models*, which represent potentially complex system behavior. While the modeling needed in our cardboard box example is likely simple, for

WEC systems, these models can range from computational fluid dynamics simulations to understanding how momentum is captured from incoming waves, to complex cost analyses that accurately predict capital, operation and maintenance, and decommissioning costs.

Within objective functions themselves as well as the contributing models, *constraints* must be obeyed to ensure realism in the optimized product or system. Typically related to the environment in which the product or system will be manufactured and used, constraints limit the potential values that design variables can take, and subsequently limit the breadth of potential evaluation of the objective function (the *feasible space*). In our cardboard box example, a constraint may be the stock size of cardboard sheet available to our manufacturers. For WEC systems, the potential constraints are numerous, and include individual constraints on the geometry of components that are represented as design variables, stability, hull footprint and weight, and the capacity of powered components.

An optimization algorithm systematically chooses new values for the design variables and tests these solutions using the objective function or functions, while ensuring that constraints are met. Solutions that evaluate well are propagated, either through the retention of good solutions or using elements of good solutions to generate new solutions. An optimization algorithm should be tuned to find globally optimal solutions (the solution with the best objective function evaluation in the feasible space). An optimization algorithm stops when new solutions do not evaluate as well as the best solution previously found. For some algorithms, this is called *convergence*, where all potential solutions are identical and evaluate better than any solutions previously identified.

In reviewing the existing body of research, we have identified that WEC optimization work spans two primary areas of optimization science: gradient search methods and heuristic methods. Gradient search methods are traditional optimization approaches that use derivatives to find improved solutions. If formulated such that the objective function is to be minimized (called "negative null form" or "standard form"), then a gradient-based search method will choose new design variables informed by the gradient of the objective function, i.e. where a negative gradient is suggesting improvement in the objective function. Gradient-based approaches stop and return a final solution when the gradient is zero, locating an inflection point in the objective function that suggests a minimum value. Most gradient-based approaches can find globally-optimal solutions (the best values for the design variables given the objective function and constraints), but can find only local optima in highly multimodal solution spaces.

Gradient-based methods are traditional search methods that are ideal for solving for the value of a single or a few interrelated design variables. Gradient-based methods are utilized prominently in controls-based WEC studies due to their fast computational time and guaranteed global convergence for convex problem formulations. Controls-based WEC studies allow for the direct calculation of derivatives, which is necessary for gradient-based search.

In contrast, heuristic optimization methods (also referred to as meta-heuristic optimization methods) are specifically designed to accommodate large nonlinear complex systems where traditional operations research methods can fall short. Common heuristic optimization algorithms include genetic algorithms (GA), simulated annealing algorithms (SA), or particle swarm optimization (PSO). GA/SA/PSO and other related algorithms can readily accommodate multiple objectives of varying linearity, and can operate under any number of realistic constraints.

Heuristic optimization methods are designed for solving complex systems, in that they are able to search large solution spaces effectively and in less time, and can be applied to problems that are unsolvable using traditional exact optimization methods such as steepest descent [41, 55]. Heuristic methods are also capable of optimizing systems represented by nonlinear, non-convex modeling and objective formulations, and can simultaneously optimize discrete and continuous variables, rendering them ideal for analyzing real-world systems such as power grids and manufacturing supply chains [24]. While not guaranteeing global solution-finding as with exact methods, heuristic optimization methods find near-optimal solutions and conduct expansive searches of large solutions spaces efficiently [18]. As such, many heuristic optimization methods have been developed and tested in the last three decades and have been applied to a host of test problems and real-world complex systems.

Heuristic optimization methods have been applied to more systems-level WEC design problems, and generally make use of multiple competing objective functions. Heuristic approaches enable the consideration of real-world concerns and generally do not require any simplification in modeling to perform. However, these high-fidelity approaches can be substantially more computationally expensive than gradient or direct search methods, and do not necessarily have guaranteed global convergence. While few WEC systems optimization studies exist currently, the ability of heuristic optimization approaches to accommodate more complex problem formulations makes them desirable.

## 1.2. REVIEW OF PREVIOUS WORK

Wave energy converters, or WECs, use the momentum and motion of ocean waves to generate electricity. While not yet widely integrated into global electricity grids, WECs are extremely promising, as they provide reliable, renewable electricity and can be located close to the majority of global population and demand centers. Designs for WECs have been proposed, developed, and tested for more than 200 years (Pierre-Simon Girard filed a patent in 1799). Over the course of this history, many wave energy conversion concepts and device archetypes have been proposed. However, to date, no single archetype has gained widespread application or acceptance.

The WEC development process has generally followed the so-called "design-build-test" framework. WEC designers and design teams currently improve a design concept iteratively using qualitative feedback and engineering design intuition. In analogous systems, such as horizontal-axis wind turbine design, developers have both converged on a small set of accepted technologies (e.g., the ubiquitous three-blade design) and have used computational design optimization to improve these concepts. Design optimization is the systematic improvement of a concept using advanced models that represent complex physical phenomena, such that design concepts are iterated automatically and improved to meet design objectives. For the design of energy generation technologies, these objective functions typically include design for maximum power development, minimized system costs, or minimized cost of energy (COE), which encompasses elements of system capital costs and selling the electricity to users.

Design optimization has contributed to substantial growth in the wind energy sector, reduction in system costs, and more accurate performance prediction. Accordingly, we see a significant opportunity to develop and apply computational optimization techniques for WECs in an effort to drive the WEC industry forward. Computational optimization can improve existing WEC designs in a more systematic, measurable way; by using optimization approaches, researchers can expressly consider multiple objectives, such as the trade-off between power development and system cost. There is also an opportunity to use advanced models that represent the state of the art in hydrodynamics, controls, and geometric representation. Moreover, studying WEC optimization can inform subsequent conversations about design convergence by offering more systematic means of comparing archetypes.

To give an informative basis for WEC design optimization tool development, in this study we explore foundational optimization science, how researchers have used optimization to design analogous systems, and previous WEC optimization studies. Through this exercise, we identify lessons learned from previous research and propose a promising and necessary path forward for WEC design optimization.

## 1.2.1. Optimization of analogous systems

To better understand the needs for applying optimization approaches to WEC design, we can look to similar systems. Three engineering systems that have analogous characteristics to WECs are considered: wind turbines, radio systems, and offshore platforms. Wind turbines were selected because they have undergone a recent progression in performance and economic viability that is often considered as a potential development pathway for WECs. Radio systems, while not mechanically or functionally similar to wave energy converters, do capture energy from waves and their design is often targeted to achieve resonance. Offshore oil and gas platforms are large ocean structures that facilitate energy extraction and are often designed for operation in energetic environments.

### *1.2.1.1. Wind turbines*

Historically, three objective functions have driven wind turbine design optimization: power coefficient ($C_p$), annual energy production (AEP), and total cost of energy (COE), which includes both capital expenditures ("CapEx") and operational expenditures ("OpEx") [13]. Power coefficient represents how much power can be extracted from the wind by the turbine, so initial design studies aimed for power maximization. However, $C_p$ varies significantly with wind speed, so design efforts shifted to maximize AEP, which takes into account some specific resource. As a final step in complexity, COE takes annual energy production and compares it with total cost of operation, rather than simply maximizing for output. As described by Chehouri et. al, a turbine blade will cost less initially if the weight is decreased, but blade reliability over time may be improved if the weight is increased [13]. In practice the use of COE has generally meant a slight reduction in power to allow for a large reduction in blade loads, accompanied by slender blades and a smaller material cost, i.e. CapEx. While there isn't a consensus on the best way to balance CapEx and OpEx, it is generally understood that only an analysis using COE, or some proxy of COE, will allow a logical basis for multi-objective design.

GAs have found much popularity in wind turbine optimization for their ability to handle complex fitness surfaces. Diveux et al. conducted a study on the implementation of a COE-driven optimization analysis using a multi-factor cost model [21]. Here, the authors considered both the price of electricity and the COE for wind turbines in an optimization analysis with a GA and evaluated them for two distinct sites: one in the Mediterranean and another in northern Europe. Comparing the two sites, the optimal Mediterranean wind turbines were found to be smaller than for northern Europe. In addition to the size, the cost of electricity was also found to be lower in the Mediterranean. This study provides an example of how local resources (wind in this case), as well as the market for the produced energy, can drive the fitness of a design.

Selig and Coverston-Carroll were among the first researchers to apply optimization to wind turbine design [52]. Prior to their work, design-by-analysis was most common, but suffered from having to account for numerous and often competing design variables. In their their study, Selig and Coeverston-Carroll applied a GA to maximize AEP while changing rotor blade length and peak power rating. Results of this study showed that, for a low-speed wind site, increasing rotor radius benefited maximum AEP more than increasing peak generator power [52]. Giguère and Selig later applied a similar GA approach to optimize blade geometry [30]. This study effectively extended the work to include noise in the objective function in addition to the COE.

In addition to GAs, PSOs and other heuristic algorithms have been successfully applied to wind turbine design optimization [56, 12]. Optimization has also been used to improve the operational control of wind turbines. At the device level, this includes control of blade pitch and generator torque. Work has included the application of many gradient based methods, as well as heuristic methods including evolutionary algorithms and PSO [37, 36, 7].

#### 1.2.1.2. Radio systems

Radio systems capture electromagnetic waves through an antenna which is converted into usable data by the receiver. The technology extracting energy from electromagnetic waves creates a myriad of opportunities. Some include benefits to product design, transferring power wirelessly over distances, and self-powering [50]. Much like WECs, radio systems are designed to resonated based on some fluctuating input signal. Two types of design optimization problems for radio systems revolve around power transmission and energy harvesting [57, 50, 44].

An objective function found for these systems is the efficiency of the antennas, also called the aperture, which is the ratio of the power delivered to the load and the power density of the source [57, 50]. Antenna design is one way to drive the performance of these systems. Roscia et al. implemented a hybrid heuristic method of a GA and PSO to couple the optimization of antenna design to the power performance of the system [50]. Gradient based methods have also been successfully applied to radio systems optimization[57, 44].

#### 1.2.1.3. Offshore platforms

Offshore platforms must be robust and reliable to perform a variety of purposes, including renewable and non-renewable energy extraction, conversion, transmission, and containment of both workers and machinery [54]. Designs for offshore platforms include floating and fixed structures for both shallow and deep water applications. One of the first attempts to design offshore structures was made by Chou in 1977 that proposed an analytical procedure for the optimal design for the structures that solved a minimization problem by calculus of variations[14]. A set of distinct platform archetypes have arisen to fit the varying environments these structures are being built in. These include jackups, gravity-based structures, tension leg platforms (TLPs), semi-submersibles ("semi-subs"), and floating production storage and offloading

(FPSOs). This utilization of distinct archetypes within the offshore oil and gas industry is interesting when considering the wide variety currently seen within the WEC design space.

Optimization of offshore platforms has both improved designs and provided designers with insights into principles that drive design performance. Clauss and Birk used nonlinear programming (NLP) to expand on the work of Chou to optimize a gravity-based structure, a TLP, and a semi-sub design to minimize loading and responses while constraining the design for hydrostatic stability [15]. Long term wave statistics were incorporated to inform the NLP algorithm to more efficiently test the extreme responses on these structures. Lee et al. applied coupled frequency and time domain analyses using a GA and sequential quadratic programming (SQP) to optimize a TLP hull form [39]. Zhang et al. utilized a GA to better understand design principles for decreasing fatigue in TLP tendons[62].

In 2017, Al Hamaydeh et al. utilized a GA with "domain-trimming" to optimize wind turbine support structures [3]. Both member size optimization and complex least-weight topology are considered by the GADT, which was validated using the benchmark 10-dimensional truss problem. Design variables consist of truss member cross-sectional areas and end node coordinates, while maximum member stresses and node displacements are the constraints. Two design alternatives, tripod and quadropod jackets, showed optimal solutions as a result of the GADT.

The semi-submersible structure is a popular design, particularly for offshore oil and gas development [34]. However, the semi-submersible must have a light substructure to account for the small water plane area. Jang et al. chose the steepest descent method for numerical optimization with a sequential group-by-group approach.

Yamamoto and Morooka evaluate the dynamic positioning system (DPS); the DPS controls platform surge, sway, and yaw [61]. The DPS must keep a stationary platform, with a tolerance radius of 2-6% to the water depth. Yadav et al. also optimized DPS by use of an improved harmony search (IHS) algorithm [60]. IHS is a meta-heuristic method based on music theory; specifically, the improvisation of a musician to continuously improve their pitch for better harmony. Compared to sequential quadratic programming, IHS saves about 51% total power consumption for the DPS.

TPLs are another popular structure for floating offshore energy production; TLPs feature tendons that are moored at each corner and have high axial stiffness, which minimize vertical motion and subsequent downtime [22]. However, TLP design must be robust to suppress movement in the horizontal and vertical directions to avoid high bending moments and axial loads. Du Kim and Jang utilize multi-objective optimization with objective functions of maximum heave response and total weight [**?**]. The study concludes, based on a Pareto set of eight solutions, that cross-sectional area of the tendons and pontoon volume are the strongest contributors to the aforementioned objective functions.

Brogran and Wasserman use risk-based, hydrostatic, and hydrodynamic analyses to measure the vortex induced vibration (VIV) of a TLP [10]. Because many TLPs operate in hostile wave environments, VIV potential is ever-present and causes fatigue damage that can escalate to component failure. The authors highlight a need for VIV effects to be considered during design of the structure, rather than after costly damage has occured. A 2012 design called Windstar TLP was created with environmental conditions of the OC3-Hywind and physical dimensions of the NREL 5 MW offshore wind turbine [63]. The numerical tool FAST performed aero-hydro-servo-elastic coupled analysis that was able to prevent rotor excitation-based resonance. Comparison to other TLP studies confirmed a lighter and smaller structure that holds up well in extreme weather conditions.

### 1.2.2. Key concepts for WEC design optimization

As with wind turbine, radio system, and offshore platform design, it is common to explore multiple design objectives to better represent stakeholder interests. One primary objective function that must be considered in the design optimization of a WEC is the performance of the device. Previous researchers have emphasized that WEC performance should be measured in terms of the economic viability of the WEC concept. The most common metric used to assess economic viability is COE, which is commonly defined by the levelized cost of energy (LCOE), which provides an estimate of the cost of electricity to the consumer without any incentives or subsidies. LCOE models can be complex, but they generally represent the ratio or sum of the device's costs to the benefit it provides (i.e. value of energy delivered), discounted over the device lifetime. By considering the design optimization problem in terms of LCOE, an optimization approach ensures WEC viability in terms of what is most important to developers and stakeholders.

The use of an LCOE objective is also consistent with preliminary research that suggests WEC design must be considered at the systems level. Weber et al. [59] discuss the importance of the evaluation and assessment of WEC systems in their entirety, including the parameterization of all subsystems, and the problems associated undertaking such systems-level approaches. This methodology was attempted on a Wavebob WEC, and it showed improvement of the systems engineering development process as well as an improvement of the simulation tools used for the techno-economic system optimization aspect.

WECs have a fundamentally multidisciplinary nature, with dynamics influenced by hydrodynamic, structural, hydraulic, and electrical subsystems. Additionally, WECs operate in a marine environment, and as such, the deployment, maintenance, and recovery costs of these systems can be significant. Thus, as with any other engineering system, we must carefully consider the model(s) used for optimization of a WEC. In design optimization, models relate the design parameters to the objective function or functions. For example, we can use optimization to select new values for geometric parameters of a WEC, such as the lengths of certain components (design variables), enable each new potential set of these design variables to be assessed for hydrodynamics (using modeling), the results of which are fed into the objective function (power development). Current WEC models include accurate capital, O&M, and other costs; hydrodynamic modeling, modeling of the mooring and anchoring system, modeling of the control system, and modeling the PTO.

One important consideration in WEC design and modeling is the application of control. While current WEC designs generally apply a simple damping control (i.e., the braking force/torque is proportional to the velocity of the device), research increasingly shows the potential of applying control to the generator system which increases the frequency range over which the WEC resonates in the waves (see, e.g., [32, 17]). In practice, this requires that in addition to some proportional damping reaction, the PTO must also apply some reactive input (i.e., the PTO works in both "braking" and "motoring" modes). This aspect of WEC design is important when considering design optimization. Since optimal power absorption[1] occurs under resonance, WEC design to maximize power absorption is effectively a tuning exercise. When we consider only a damping control, this means that for longer, lower frequency waves, the device should be larger; for shorter, higher frequency waves, the device should be smaller. The problem changes when reactive controllers are included. When the control input can be used to shift the resonance of the device

[1]Note that power absorption refers to the mechanical work done by the WEC, not electricity. This is an important distinction.

(i.e. instead of simply making the hull larger or smaller), the optimization problem changes completely [45]. This is a key consideration that has been considered in only a small subset of WEC optimization studies [45, 1, 26, 31].

When researchers consider optimization in the context of control, they often think of so-called receding horizon methods, such as model predictive control (MPC). Many studies have applied MPC to WECs (see [19, 40, 32]). However, optimization can also be considered in the design of a control algorithm. The difference between these two frameworks is important, particularly for the current discussion. Examples of each type of approach are discussed by [16]. For receding horizon control, the control input for the system is iteratively optimized based on predictions over a some finite future time. In practice, this requires that the optimization be implemented for real-time execution. Offline optimization, in which optimization is used to determine the value of control tuning/gain parameters, does not have this constraint. Examples of this include tuning of simple PID controllers and linear quadratic control (see, e.g., [51]).

At the device design stage, we are concerned not about the real-time implementation of a controller (i.e., programming the logic into some real-time target for it to operate in wave tank or at sea), but instead about the understanding the performance potential of the overall design. Thus, in the present study, our interest is on optimization as a design tool for control algorithms. Considering only this need, we can review the maximum power transfer law that is the basis for all WEC control (see, e.g., [23]).

This relies on the linearization of the WEC dynamics into the form

$$\begin{aligned}\left[i\omega\left(M+m(\omega)\right)+B_v+R(\omega)+\frac{S}{i\omega}\right]v(\omega)\\ =F_e(\omega)+F_{pto}(\omega).\end{aligned} \tag{1.1}$$

Here, $\omega$ is the radial frequency, $M$ is the rigid-body mass, $m(\omega)$ is the hydrodynamic added mass (which is frequency dependent), $B_v$ is the viscous damping, $R(\omega)$ is the radiation damping, $S$ is the stiffness used to represent the balance between hydrostatic and gravitational forces, and $v$ is the velocity the WEC. On the right-hand-side of (1.1), $F_e(\omega)$ and $F_{pto}(\omega)$ are the wave excitation and power take off (PTO) forces, respectively.

From the left hand side of (1.1), we can define the intrinsic impedance for the WEC as

$$Z_i(\omega)=i\omega\left(M+m(\omega)\right)+R(\omega)+B_v+\frac{S}{i\omega}, \tag{1.2}$$

such that

$$\begin{aligned}Z_i(\omega)v(\omega)&=F_e(\omega)+F_{pto}(\omega)\\&=F_{\text{ext}}(\omega).\end{aligned} \tag{1.3}$$

Solving for the complex velocity $v(\omega)$, we have

$$\begin{aligned} v(\omega) &= \frac{F_{\text{ext}}(\omega)}{Z_i(\omega)} \\ &= \frac{F_{\text{ext}}(\omega)}{\left(i\omega\left(M + m(\omega)\right) + R(\omega) + B_v + \frac{S}{i\omega}\right)}. \end{aligned} \tag{1.4}$$

If we define some impedance, $Z_{pto}(\omega)$ for the PTO force, such at $F_{pto}(\omega) = -Z_{pto}(\omega)v(\omega)$, the useful time-averaged power absorbed will subsequently be

$$\begin{aligned} P_{pto}(\omega) &= \frac{1}{2}\mathbb{R}\left\{-F_{pto}(\omega)v(\omega)\right\} \\ &= \frac{1}{2}\mathbb{R}\left\{Z_{pto}(\omega)\right\}\left|v(\omega)\right|^2. \end{aligned} \tag{1.5}$$

Control design is effectively determining the definition of $F_{pto}(\omega)$, which in our current formulation is defined by $Z_{pto}(\omega)$. For resonance, it can be shown that maximum useful power is obtained by setting

$$Z_{pto}(\omega) = -Z_i^*(\omega), \tag{1.6}$$

where $^*$ denotes the complex conjugate.

In practice, $F_e(\omega)$ is non-causal, which means that implementing (1.6) can not be accomplished in the exact sense. However, this is of little concern for our present interest. Since we are primarily focused on understanding the performance *potential* of a WEC design, it is sufficient to find the performance that would be produced by directly implementing (1.6) and leave the approximation of this will result in a relative similar performance.

However, the validity of this approach is limited by the physical implications of (1.6). While this so-called "complex conjugate control" will always maximize mechanical power absorption, this is not necessarily the desired outcome. We are more interested in generated power (or even better, power delivered to the grid) than absorbed power. Additionally, as pointed out by [11], (1.6) sometimes requires that the WEC motion be extreme (e.g., vertical displacements that exceed the WEC's draft).

Considering this, we desire a way of understanding the potential performance of a WEC with control design that increases energy generation without violating some physical limits. The pseudo-spectral control design approach developed by [6] and applied in some preliminary optimization studies [1, 45] presents an attractive solution. This allows for efficient evaluation of a dynamic system which can include nonlinearities, such as limits on displacements.

### 1.2.3. WEC optimization work to-date

While WECs have not been the subject of design optimization studies to the same degree as more developed systems, there have nonetheless been some useful pieces of work completed to-date. Table 1-1 provides a summary of studies reviewed herein. For each study, Table 1-1 lists the optimization type (either gradient-based or heuristic) as well as a description of the objective function(s) employed. Within this table, the following symbols are used to define objective functions:

**Table 1-1. Summary of WEC optimization studies to-date. (Note that two studies marked with * have been included which do not use an optimization algorithm, but instead use an exhaustive parametric search approach or are some type of trade study. The † mark indicates that volume is not directly calculated, but represented by the cube of some scaling parameter.)**

| Study | Optimization type | Objective function |
|---|---|---|
| [1] | Gradient & Heuristic | max $P_{abs}$ / $\forall$ |
| [4] | Heuristic | max $P_{abs}$; min $\forall$ |
| [53] | *Parametric search | max $P_{abs}$, match $T_n$, max $\beta$ |
| [31] | Heuristic | max $P_{abs}$ |
| [27] | *Parametric search | max $P_{abs}$ |
| [25] | *Parametric search | max $P_{abs}$ |
| [35] | Heuristic | min $A$ / $P_{abs}$, min $F_{PTO}$ / $P_{abs}$ |
| [45] | Gradient | max $P_{abs}/(1+\forall^{\dagger})$ |
| [42] | *Trade study | max $P_{abs}$ |
| [43] | Heuristic | separate cases, max $P_{abs}$, $P_{abs}/\sqrt[3]{\forall}$, $P_{abs}/\forall$ |
| [49] | Heuristic | max $\bar{C}_w$ |
| [9] | Heuristic | max $P_{gen}$; min $\forall$ |
| [8] | Heuristic | max $P_{gen}$, min $A$ |
| [2] | Heuristic | max $P_{abs}$ |
| [29] | Heuristic | separate cases, max $P_{abs}$, $P_{abs}/\forall$, % change in LCOE |
| [28] | Heuristic | separate cases, max $P_{abs}$, $P_{abs}/\forall$ |

- $P_{gen}$ - Generated power
- $P_{abs}$ - Absorbed power
- $\forall$ - Displaced volume
- $A$ - Hull surface area
- $T_n$ - Natural period
- $\beta$ - Bandwidth
- $\bar{C}_w$ - Average capture width ratio

A variety of objective functions have been applied in WEC optimization. From Table 1-1, we can see that the majority of studies to date have considered power absorption as the only objective function. Others have used ratios of absorbed power to a proxy for LCOE, e.g., volume [1, 29, 28, 43], or hull surface area [8, 35]. Rather than use volume as a proxy for LCOE, the authors of [45] used a simple function of the scaling parameter in their objective function.

$$\frac{P_{abs}}{1+\lambda^3} \tag{1.7}$$

Here, $P_{abs}$ is average absorbed power over some period and $\lambda$ is a linear scale parameter. The concept of (1.7) is to capture some $1^{st}$-order behavior of cost as a function of volume in denominator, thus balancing the benefit gained by collecting additional energy. Some studies have utilized multi-objective approaches to maximize power and minimize volume [4, 9] or to minimize surface area [8, 35].

The authors of [43] looked more carefully at the impact of objective functions in WEC optimization. In this study, the author considered three separate objective functions of power ($P_{abs}$), the ratio of power to displaced volume ($P_{abs}/\forall$), and the ratio of power to the cube root of displaced volume ($P_{abs}/\sqrt[3]{\forall}$). Others compared the use of volume to hull surface area as the LCOE proxy [8]. Both studies indicate that optimized WEC designs are very sensitive to the objective function and the LCOE proxy chosen. In the case of LCOE proxies, hull surface area exacts a more stringent "size penalty" than volume [8]. While widely used in wave energy, capture width, which measures the efficiency of a WEC, has not been widely used in design optimization. Capture width ratio, which normalizes the capture width by the device dimension, provides an attractive optimization metric. However, [49] uses capture width ratio to optimize a flat-type surging wave energy converter for a specific location and compare it with past Oyster prototypes. Garcia-Teruel et al. investigated other cost parameters with an effect on shape, such as manufacturability in [29], and the effect of the combination of modes of oscillation on optimal WEC shapes while optimizing for maximal annual energy production and for the ratio of annual energy production to submerged volume [28]. Results from these studies point to the limitations of using volume as proxy for costs. With a parametric search approach using Design of Experiments, [53] aimed at finding a cylinder shape that maximizes power performance at the energy period but simultaneously has a wide resonance bandwidth. By defining many constraints and relationships between different metrics, and giving a weighting to the various objectives a preferred radius and draft was found for a location at the coast of Rio de Janeiro.

As discussed in Section 1.2.2, control can play a major role in determining the overall performance of a WEC design. However, to-date the majority of studies on WEC design optimization have not considered control in detail. Instead, most studies have applied a simple damping control, while often acknowledging this as a shortcoming. Some exceptions include studies in which optimal impedance matching control was assumed [43, 45, 29, 28]. Sub-optimal but perhaps more realistic strategies, such as latching control [31] and stroke limited reactive control [45, 1], have also been applied. In particular, a handful of these studies have specifically considered the effect that utilizing a more complete control design has on overall device design optimization [31, 45]. The general conclusion from these studies is that control design must be included in the larger device design optimization process (this is often referred to as "co-design"), because control design can have a considerable effect on the resulting optimal shape and on the overall device performance.

A number of different geometric representations have been used for WEC hull optimization. These fall into two categories: cases in which dimensions of some predefined shape are optimized and cases in which some parametric surface (such as Bézier surfaces or splines) are used. Both of these approaches have been considered for WECs. The size of predefined hulls has been considered by many studies. These have included simple cylinders [31], as well as scaling of more complex shapes as in the case of the Reference Model 3 [45]. The authors of [1] use both Bézier curves and polynomial functions of various orders to define an axis-symmetric body, and conclude that Bézier curves are capable of providing better results. In [43, 29, 28] a bi-cubic B-spline surface is used for a very flexible geometry definition. The authors of [29] obtained results by this very flexible geometry definition which are compared to results for a geometry defined from a design for manufacturing point of view - made out of rolled steel sheets, common in ship hull manufacturing.

### 1.2.4. Conclusions and identification of critical needs

Given the relative youth of the WEC industry and significant variation in commercial WEC concepts, there are currently no available tools or even widely accepted approaches for systematically optimizing WEC concepts. While much work has been done to develop new concepts and mature those concepts to a high readiness-level, it is very likely that optimally performing designs are not being realized due to a failure to apply a systematic optimization process which synchronously considers system dynamics and control. That is, while many good concepts have been developed, the detailed design and maturation of WECs often results in a far from optimal solution due to the disjointed nature by which the major WEC components and design steps are integrated (e.g., hydrodynamic design is considered separately from control design). The consequence, in terms of reduced energy capture, increased loading, and overdesign, has likely been an increased LCOE for WECs.

Many well-engineered mechanical devices have similar characteristics to WECs, including wind turbines, radio frequency systems, and offshore platforms. Such analogous mechanical devices have undergone both direct and heuristic optimization processes throughout their development, and have benefited from this work. To avoid costly design mistakes in WEC optimization, consideration of these analogous devices should provide a foundational understanding of how optimization works. Primarily, history has shown that designing devices for one objective often doesn't necessarily provide the best solution, and that multi-objective design allows for a more holistic optimization.

Wind turbines, radio frequency systems, and offshore platforms have all been optimized successfully via several types of multi-objective algorithms; the genetic algorithm (GA) is common among them. Furthermore, optimization of wind turbines has seen particularly good success with multi-objective algorithms in recent years. These past successes, coupled with the need to produce efficient low-cost energy, point to heuristic algorithms as the best available tool for WEC optimization.

Based this review, we have distilled the following as best-practices and areas for additional consideration moving forward:

1. **Key WEC optimization parameters** - When considering hull optimization, Bézier curves have proven to be the most efficient and effective approach for "free-form" parametric geometry. However, it may also be useful to simply consider some scaling of pre-defined shapes. Other key parameters include specifications for the PTO system, such as power rating, power stroke, and control design.

2. **Key objective functions** - It has been shown that optimized WEC designs are sensitive to the objective functions and cost proxies chosen. It is, therefore, important to investigate the sensitivity of the optimized WEC design to different objective functions and cost proxies. Volume is not a good proxy for costs because XX it (over-/under-penalizes for WEC size); Othe proxies for costs need to be studied further; including ways to better calibrate these proxies to actual LCOE. For power, in addition to maximizing power generation, it will also be important to consider smoothness, capacity factor, and peak-to-mean ratios.

**Table 1-2. WEC Optimization Tool releases.**

| Version | Design variables | Optimization algorithm(s) | Device(s) considered | Public release? | Notes |
|---|---|---|---|---|---|
| alpha | Single scaling factor | MC | RM3 | No | |
| beta | Seven design parameters | EPS, GA, MC, CMA-ES | RM3 | Yes | |
| v0 | Generalized | EPS, GA, MC, CMA-ES | Generalized | Yes | |
| v1 | Generalized | EPS, GA, MC, CMA-ES | Generalized | Yes | Improved usability and robustness |

3. **Multi-objective optimization** - Using a multi-objective optimization approach removes/reduces the need for the engineer to make subjective decisions in the definition of complex cost functions.
4. **Tuning** - Since hull design, PTO design, and control design are all strongly coupled factors which can "tune" device dynamics, these components must be considered synchronously in a "co-design" approach to achieve the best possible designs.
5. **Heuristic and gradient based optimization** - Heuristic algorithms provide the flexibility needed to handle multi-objective nonlinear design problems. However, using gradient based and heuristic methods in conjunction can sometimes improve on only using the heuristic method.

# 1.3. PROJECT OUTLOOK

This project is targeted developing an open-source tool for the optimization of WEC design commercial viability. Table 1-2 shows a planned progression for the tool. Version alpha will allow for verification of the code via systematic verification of a small (single design variable) problem. The beta version will support the development of a case study on the RM3 device (see Section 3) and allow for initial open-source usage. Versions v0 and v1 will provide a generalized tool applicable to any resonant WEC. Version v1 will extend the usability and robustness of v0.

# 2. IMPLEMENTATION

This chapter summarizes the implementation of the WEC design optimization tool. First, a general architecture of the algorithm is discussed, followed by discussions of individual steps (or "blocks") within this algorithm. Next, some details on the code implementation in MATLAB are provided.

## 2.1. ALGORITHM ARCHITECTURE

Figure 2-1 shows a diagram of the architecture of the WEC design optimization tool. This diagram is drawn with some blocks specific to the RM3 case-study discussed in Chapter 3, but the general structure is valid for any application of the tool. Designs, defined by a set of design variables, are generated in the upper left-hand corner and are evaluated by the sub-blocks within the large grey rectangle.

## 2.2. ALGORITHM MODULES

### 2.2.1. Optimization algorithm

Based on the application of optimization methods in similar and related work, and on the nature of the problems[1] considered in this project, the following optimization algorithms were selected:

- **Monte Carlo** A statistical based algorithm used to model probabilistic or stochastic systems and establish the odds of a variety of outcomes.
- **Genetic Algorithm** An initial population of potential solutions are generated and evaluated for evolutionary fitness. Mimicking the biological process of passing chromosomes from parents to children, crossover and mutation occur at each iteration to expand the solution space and avoid local optima.
- **Extended Pattern Search** A variant of a traditionally deterministic pattern search algorithm that employs stochastic elements to aid the search in escaping local optima. The random initial solution is passed through user-defined pattern directions and selects the superior evaluation at each step size.

[1] Note that multiple optimization problems are considered to be of interest in this project. In particular, problems with entirely continuous design variables are considered, but problems with discrete design variables, in order to handle, for example, discrete generator models, are also considered relevant.

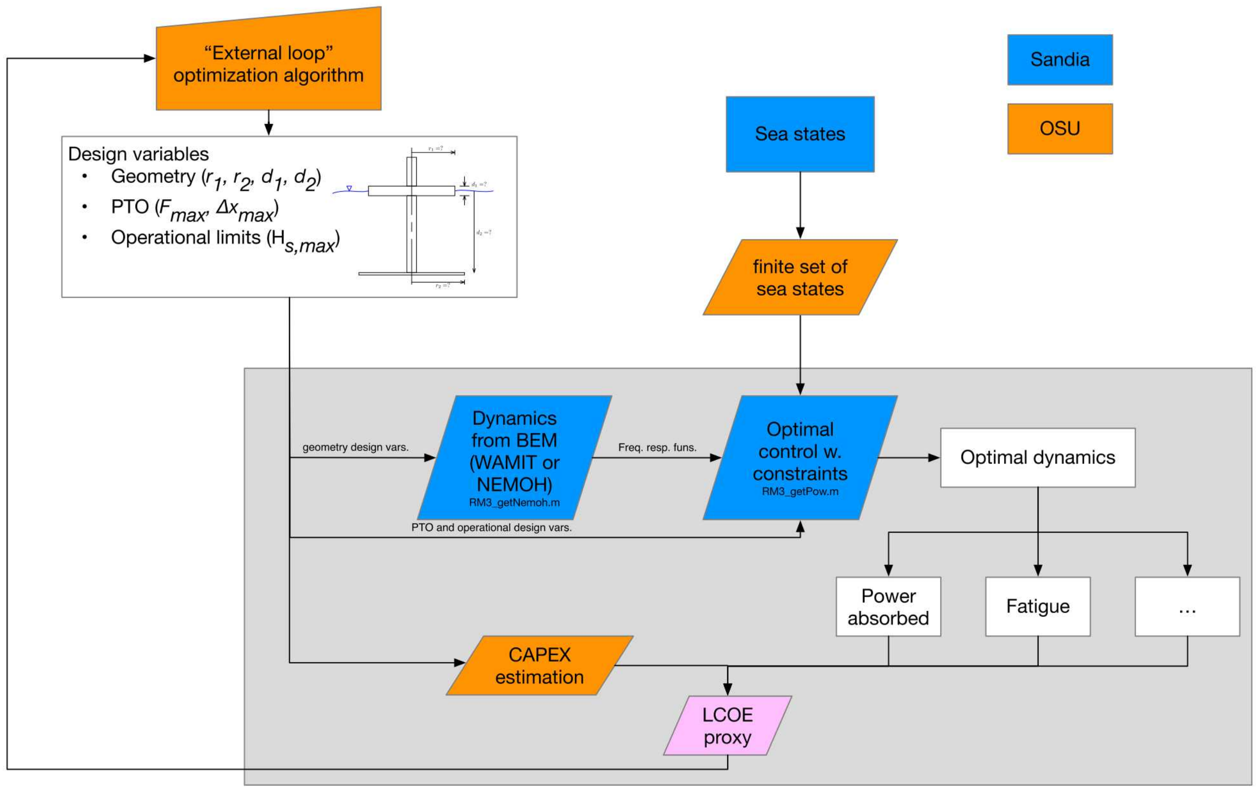



**Figure 2-1. Diagram of WEC design optimization algorithm architecture.**

- **CMA-ES** - Covariance matrix adaptation evolution strategy (CMA-ES) is a stochastic derivative-free optimization method well-suited for nonlinear and non-convex continuous optimization problems [33].

## 2.2.2. Meshing and boundary element analysis

A simple wrapper for the open-source boundary element solver NEMOH [5] is implemented in MATLAB. This tool is currently suitable of axisymmetric devices with $n$-bodies and is built from previous work by [48]. The general steps are as follows:

1. **Parametric description of geometry:** The geometry for the hull must be described by some finite set of parameters.

2. **Meshing:** The surface of the hull must be discretized; this is accomplished via the `aximesh.m` MATLAB tool that comes with NEMOH.

3. **BEM problem setup:** The necessary problem setup parameters, such as frequencies at which to evaluate the solution, degrees of freedom, and output selection, must be specified.

4. **Solver:** The NEMOH solver and post-processor are run.

5. **Parsing:** The results from NEMOH are parsed from text files by the WEC-Sim [38] function `Read_Nemoh.m`.

### 2.2.3. WEC modeling & control

Modeling of WECs in the WEC Optimization Tool relies on the widely utilized linear approximation for a floating body (see, e.g., [23]).

Three interchangeable control approaches are implemented in the WEC design optimization tool.

- **Resistive damping** - This controller implements maximum power for a resistive damping (proportional velocity) control.
- **Complex conjugate control** - The optimal mechanical power absorption is achieved via impedance matching (see, e.g., [23]).
- **Constrained complex conjugate control** - This approach uses a pseudo-spectral method to solve for the optimal control give some set of input and state constraints [6].

The constrained complex conjugate control approach is considered the most realistic and relevant in terms of design optimization. Note that this approach is considered a "stand-in" for the purposes of design optimization. The results produced by using the constrained complex conjugate control pseudo-spectral solver will be similar to whatever controller is eventually implemented, whether it be some feedback based control or a controller that relies on wave prediction [17]. Using this stand-in approach allows for the dynamics of the controller to influence the design optimization without requiring detailed implementation early in the design process.

### 2.2.4. Objective function

The objective function utilized in the WEC Optimization Tool is intended to provide some representation for commercial viability of the design. In this project, some focus will be given to investigating the best means of formulating such an objective function for a WEC. However, especially with respect the case study of the RM3[2], the amount of resources committed to this endeavor will be limited, as it is envisioned that the specific formulation will depend heavily on the specific device. Given the high degree of variability amongst WEC designs under consideration today, it follows that objective functions for these design may also vary substantially as well. Thus any work in this area will be targeted at providing generalized findings suitable for guiding objective function formulation for WECs in general.

While it is important to optimize the power generation of the device (and to understand how this power metric changes with variation in the design variables), simply maximizing power generation in an optimization scheme will lead to solutions that are *trivial*. While it is generally desirable to produce more power, this does not exclusively define the suitability of a design. In many renewable energy studies, optimizing device design with the objective of minimizing costs (or Levelized Cost of Energy, LCOE) are very common and give researchers and stakeholders a clear understanding of the cost of these technologies to

[2] See Sections 3 for some initial objective functions applied to the RM3

power consumers. However, accurately predicting LCOE for a WEC concept is challenging due to the relative youth of the market and the high degree of variability between WEC designs.

Due to this, we propose investigating multiple objective function formulations during this project. Using volumetric values, such as surface area or device volume, can give a preliminary understanding of the costs and manufacturability of a device concept.

# 3. INITIAL RESULTS

## 3.1. INTRODUCTION

As discussed in Section 1, the RM3 device is considered for a case study to assist in the development of the WEC Optimization Tool. Figure 3-1 shows a schematic for the geometric design variables considered for the RM3. Additionally, PTO design variables and operational design variables were considered. Table 3-1 shows a full listing of design variables and their constraints.

To better understand the design problem at hand, a sensitivity study was conducted. Using a latin hypercube sampling, 1e3 designs within the bounds of Table 3-1 were created and evaluated. For each design (i.e., set of design variables), the following responses were calculated:

- Power using damping control, $P_P$
- Power using complex conjugate control, $P_{CC}$
- Volume, $V$
- Surface area, $A$

This study is intended to provide a better understanding both of which design variables have a large impact on the design performance and also to understand which response variables (or combinations there of) could be used for objective functions.

## 3.2. SEA STATES

For this RM3 case study, a set of sea states based on the original deployment location of Humboldt Bay, CA will be considered. Figure 3-2a shows the joint probability distribution (JPD) plot from the original

**Table 3-1. RM3 case study design variables and bounds.**

| Parameter | Bounds |
|---|---|
| Float radius, $r_1$ [m] | $5 < r_1 < 12.5\,\text{m}$ |
| Reaction plate radius, $r_2$ [m] | $10 < r_2 < 17.5\,\text{m}$ |
| Float draft, $d_1$ [m] | $1 < d_1 < 5\,\text{m}$ |
| Reaction plate depth, $d_2$ [m] | $32 < r_2 < 47\,\text{m}$ |

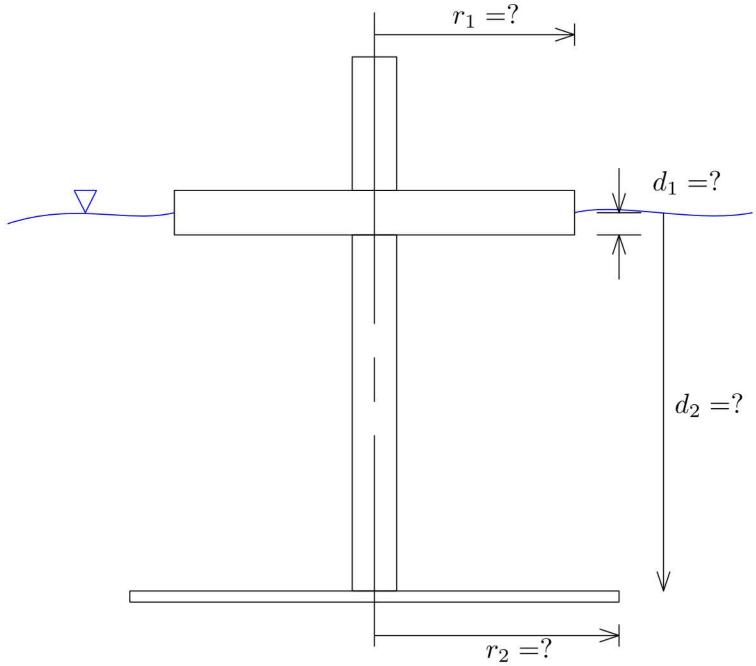



**Figure 3-1. RM3 geometric design variables.**

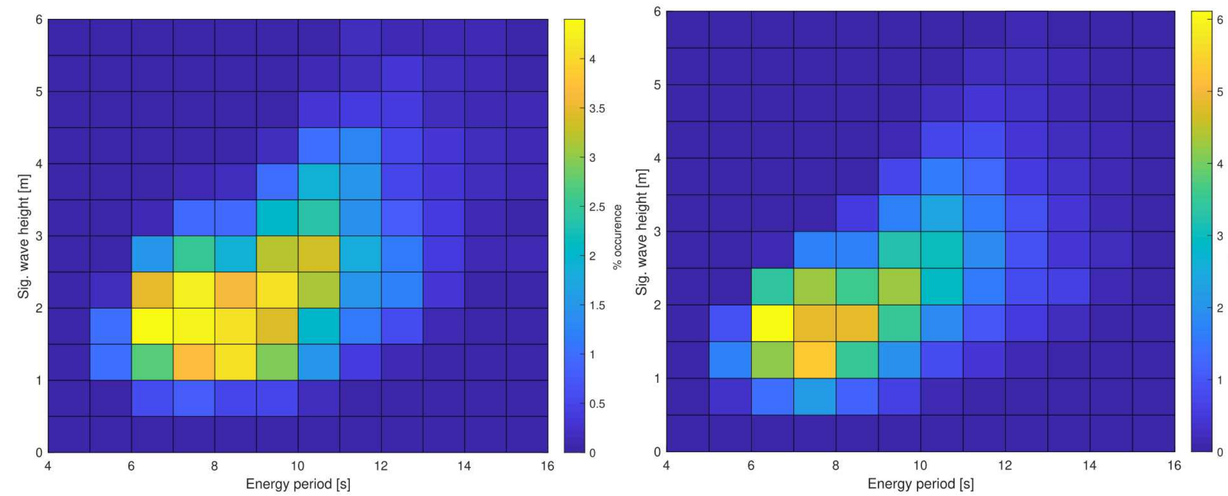
RM3 design report [46], which was compiled based on 54 months of data. Subsequently, [20] provided a more extensive assessment of site using ten years of hindcast model data (Figure 3-2b).

For the results presented in this scoping report, a single sea state was chosen for analysis. Based on the JPDs shown in Figure 3-2, a sea state with an energy period of $T_e = 7.5\,\mathrm{s}$ and a significant wave height of $H_s = 1.75\,\mathrm{m}$ was chosen as this single sea state. Based on the comparisons with average spectral distributions observed in data for the Humboldt Bay site [20], a Bretschneider wave spectrum generated using WAFO [58] was employed. Note that in future work, a set of sea states will be used to provide a more comprehensive representation of the wave climate.

## 3.3. RESULTS

Figure 3-3 shows the results from the sensitivity analysis for the RM3. These response variables are considered to form some set which may be used later on to compose objective functions for optimization. In Figure 3-3, the results for a single response variable is shown across a single row. For example, all of the plots along the top row of the figure show the power using complex conjugate control. The response on each y-axis are normalized by the median response. The four design variables ($r_1, r_2, d_1, d_2$) correlate with the four columns in Figure 3-3. In each plot, the results from the analysis are shown with blue points along with a linear trend (red line). The slope and fit ($r^2$) for the line are also shown.

It is interesting to compare the two power response for the $r_1$ design variable. We can see that the power from complex conjugate control ($P_{CC}$) is not strongly linked to $r_1$. However, the power from damping ($P_P$) is strongly correlated to $r_1$. This result illustrates an important point. Since the complex conjugate control, which is not realistic in that it violates physical limits, can achieve perfect absorption around




**(a) Reference Model Report (54 months) [46].** **(b) Dallman & Neary (10 years) [20].**

**Figure 3-2. Resource assessments for RM3.**

the resonance of the device, changing $r_1$ has no effect (i.e., there is no room for improvement). With damping control however, we can see the stronger effect that we suspect – that is that power is increased with increases in $r_1$.

By looking in the far right column of Figure 3-3, we can see that, for the range of values considered, the depth of the reaction plate, $d_2$, has relatively little effect on the response variables. At the least, this would indicate that the range of potential values for $d_2$ should be reconsidered. However, it may also mean that $d_2$ should not be included as a design variable.

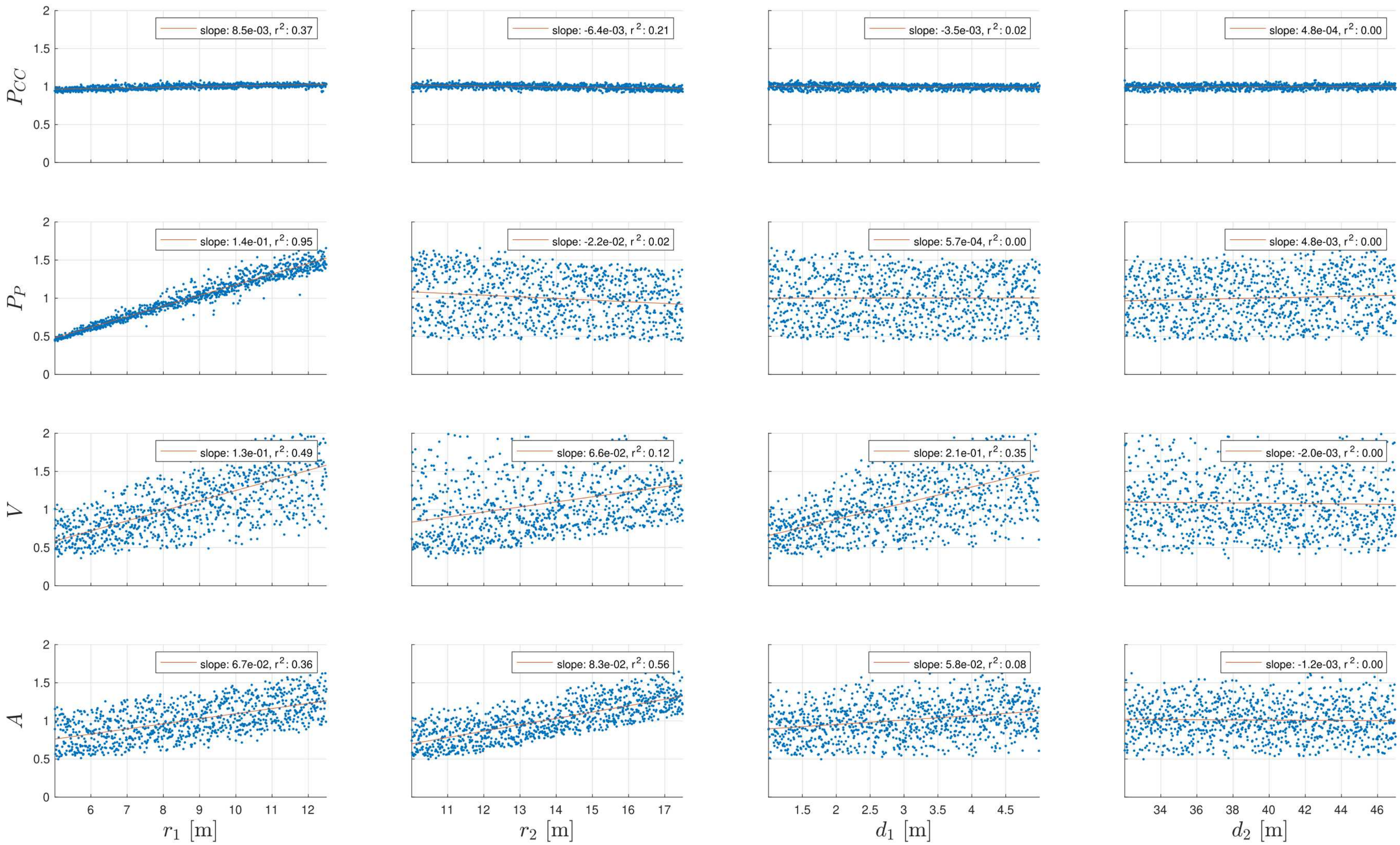



**Figure 3-3. Sensitivity analysis for RM3 design optimization.**

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