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### Permalink

<https://escholarship.org/uc/item/9f71n7st>

### ISBN

9781538620953

### Authors

Sunter, Deborah A  
Murray, Bryan  
Lehmann, Marcus  
et al.

### Publication Date

2017

### DOI

10.1109/DISTRA.2017.8191137

Peer reviewed

# Two-Stage Monte Carlo Simulation to Forecast Levelized Cost of Electricity for Wave Energy

Deborah A. Sunter<sup>1,2\*‡</sup>, Bryan Murray<sup>3\*</sup>, Marcus Lehmann<sup>3</sup>,  
Rachael Green<sup>4</sup>, Bryant Ke<sup>4</sup>, Brooke Maushund<sup>4</sup>, Daniel M. Kammen<sup>1,5</sup>

<sup>1</sup>Energy and Resources Group, University of California, Berkeley,  
310 Barrows Hall, Berkeley, CA 94720–3050

<sup>2</sup>Department of Mechanical Engineering, Tufts University  
204 Anderson Hall, Medford MA 02155

<sup>3</sup>CalWave Power Technologies, Inc.  
1387 Scenic Ave, Berkeley, CA 94708

<sup>4</sup>Undergraduate Research Apprentice Program, University of California, Berkeley,  
2412 Dwinelle Hall, Berkeley, CA 94720-2940

<sup>5</sup>Goldman School of Public Policy, University of California, Berkeley,  
310 Barrows Hall, Berkeley, CA 94720–3050

\* These authors contributed equally to this work.

(deborah\_sunter@berkeley.edu, bryan@calwave.org, marcus@calwave.org, rsgreen@berkeley.edu,  
bjke@berkeley.edu, brooke.maushund@berkeley.edu, kammen@berkeley.edu)

‡Corresponding Author: Deborah A. Sunter, 310 Barrows Hall, Berkeley, CA 94720, deborah\_sunter@berkeley.edu

**Abstract-** The technically recoverable global wave energy resource is estimated to be between 2 PWh/year and 5.5 PWh/year, approximately 12% and 32% of global electricity consumption. Despite wave energy's vast global potential, there has been relatively little commercial deployment to date. There is large variation in both the current estimated and future expected electricity generation costs associated with wave technologies. This paper quantifies a forecasted levelized cost of electricity (LCOE) for wave energy by performing a two-stage Monte Carlo simulation, considering both the variability in current LCOE estimates and uncertainty in the one-factor learning rate. We compare the forecasted LCOE to wave energy targets of the European Union and U.S. Department of Energy and show the criticality of support mechanisms to achieve learning rates that lead to economic competitiveness in the utility-scale markets.

**Keywords-** Wave Energy, Levelized Cost of Electricity, Monte Carlo Simulation, Renewable Energy

## 1. Introduction

The World Energy Council reported estimates of the technically recoverable global wave energy resource to between 2 PWh/year and 5.5 PWh/year, approximately 12% and 32% of global electricity consumption [1]. Despite its potential and a surge of recent research activities focusing

on numerical simulations [2]–[5], subcomponent improvements [6], [7], and integration with other renewable energy systems [8], the wave energy industry has seen comparably low commercial application in the U.S. [9] and globally [10]–[13]. The technical, environmental, and operational challenges of the wave energy industry may be analogous to those of offshore wind, though the latter has recently achieved over 14 GW of installed capacity [14] compared with less than 10 MW of wave energy [15]. The Levelized Cost of Energy (LCOE) of offshore wind has decreased along with growing capacity, approaching parity with other renewable and conventional sources [14] at a reference price of \$126/MWh [16]. This decrease in cost with increasing capacity is often expressed by a learning rate, the percentage of cost reduction for each doubling of cumulative installed capacity. Latest reports from the US and EU forecasting the LCOE of wave energy [15], [17] neither include learning rates in their sensitivity analysis nor transfer industry trends reported in the offshore wind industry. This paper aims to do both. Using the trends in the deployment and learning rate of offshore wind, this paper explores the potential evolution of the wave energy sector. After forecasting the LCOE of wave energy, implications for the industry potential and possible government tools to assist in reaching this potential are discussed.

## 2. Methodology

### 2.1 Current Estimates of Wave Energy LCOE

Published estimates of wave energy LCOE vary widely [15], [18]–[20]. Several factors contribute to this variation. First, in contrast to the three-blade standard for wind turbines, there has been no convergence to a standard wave energy converter topology. Second, deployments to date have been short, and often at less than nominal full scale, as “proof of concept” demonstrations rather than tests of commercial-ready devices. Finally, the total installed capacity has simply been too low to draw generalizations regarding costs. Despite these limitations, several LCOE estimates have been made; three are summarized in Table 1. It is important to note that these estimates are for early stages of wave energy development (<10 MW of cumulative installed capacity).

*Table 1. Wave Energy LCOE Estimates in 2016USD/MWh at 10MW cumulative installed capacity.*

Source	Median LCOE Estimate	High LCOE Estimate	Low LCOE Estimate
JRC 2016 [15]	676	773	580
IEA 2015 [18]	707	1010	505
UK ERC 2014 [19]	559	799	319
Carbon Trust 2011 [20]	663	740	586

The first stage of the Monte Carlo simulation takes the current variability in wave energy LCOE into account. Using the parameters from Table 1, for each source we assume a Gaussian distribution for LCOE estimates centered at the median with both the high and low estimates of LCOE assumed to be within two standard deviations of the median, as can be seen in Fig.1a. Recognize that some LCOE estimates are skewed, resulting in variations in the high and low standard deviations. To generate a single distribution for the current wave energy LCOE, we performed a Monte Carlo simulation with a total of 12,000 samples taken equally from each source. The resulting distribution of current wave energy LCOE estimates is shown in Fig.1b

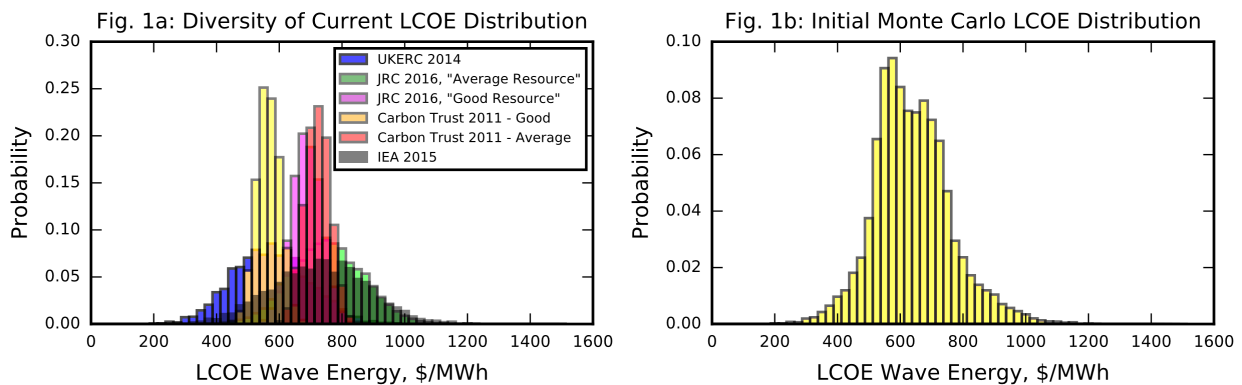


Figure 1. (a) Gaussian distributions of reported LCOE estimates for 10 MW installed capacity. (b) LCOE distribution used in the Monte Carlo simulation based on reported LCOE estimates for average wave resource [15], [18]–[20].

## 2.2 Deployment and Learning Rates

Offshore wind grew relatively slowly at first with accelerated deployment as cost uncertainties decreased through the standardization of fabrication, deployment, and operations [21]. The global offshore wind industry experienced a compound annual growth rate (CAGR) of 38.1% [14], [22], as shown in Fig.2a. Taking the current cumulative installed capacity of wave energy to be 4.4 MW [15], we assume the same CAGR as offshore wind.

With increased deployment, the LCOE for offshore wind decreased. This reduction has been modeled with a single-factor learning rate, with reported learning rate estimates of 5% and 19% [23]. Assuming these estimates represent the 95% confidence interval for the learning rate of wave energy, and assuming a normal Gaussian distribution between these bounds, a second Monte Carlo simulation was used to create the distribution of learning rates for wave energy seen in Fig.2b. Others [21] have also assumed a 12% learning rate directly for wave energy.

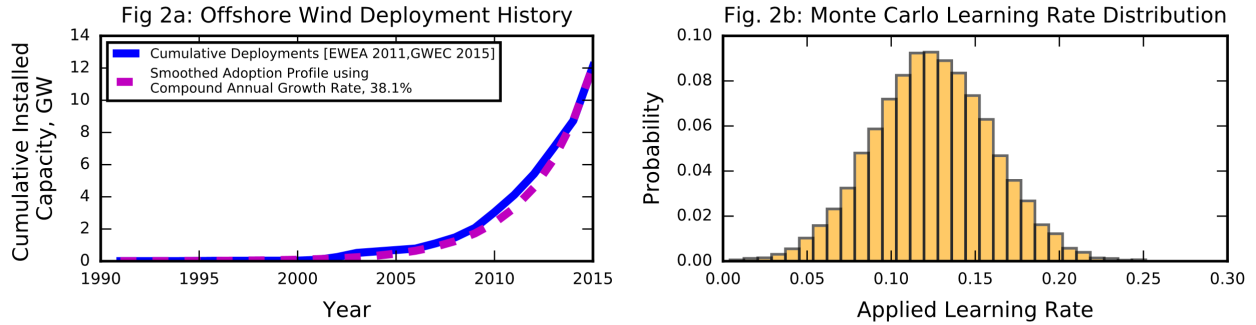


Figure 2. (a) Historical deployment of offshore wind [14], [22]. (b) Learning rates used in the Monte Carlo simulation.

### 2.3. Two-Stage Monte Carlo Simulation

The two-stage Monte Carlo simulation considers both the variability in current LCOE estimates and uncertainty in the one-factor learning rate. Each of the 12,000 simulated current LCOE estimates shown in Fig.1b was paired with a randomly sampled learning rate from Fig.2b. Together, these were used to determine the 95% confidence interval for the LCOE of wave energy as a function of installed capacity. Using the CAGR from offshore wind, the LCOE of wave energy as a function of time is used to assess government targets. The program developed to execute the two-stage Monte Carlo simulation has been made available on GitHub [24].

## 3. Results

### 3.1 Levelized Cost of Electricity and Installed Capacity

The results of the wave energy LCOE forecast as a function of installed capacity using the two-stage Monte Carlo simulation show strong agreement with estimates from surveyed wave energy developers [18]. Through stakeholder engagement, the IEA [18] established three development phases: i) first pre-commercial array, ii) second pre-commercial array, and iii) commercial scale target. The surveyed developers thought the second phase would occur after 40 MW of cumulative installed capacity of wave energy technologies and the third phase after the current LCOE of wave energy was reduced by 75% [18]. The range of the developers' responses for these two phases can be seen in yellow and green in Fig. 3a.

Targets for wave energy LCOE reduction have been published by both the European Union and U.S. Department of Energy. The EU target is \$220/MWh by 2030 [15], while the US target is \$168/MWh by 2030 [17]. These targets are shown in Fig. 3b. The average of the 12,000 Monte

Carlo simulations suggests that these targets could be met after cumulative global installed capacity has reached 2.9 GW and 15 GW, respectively.

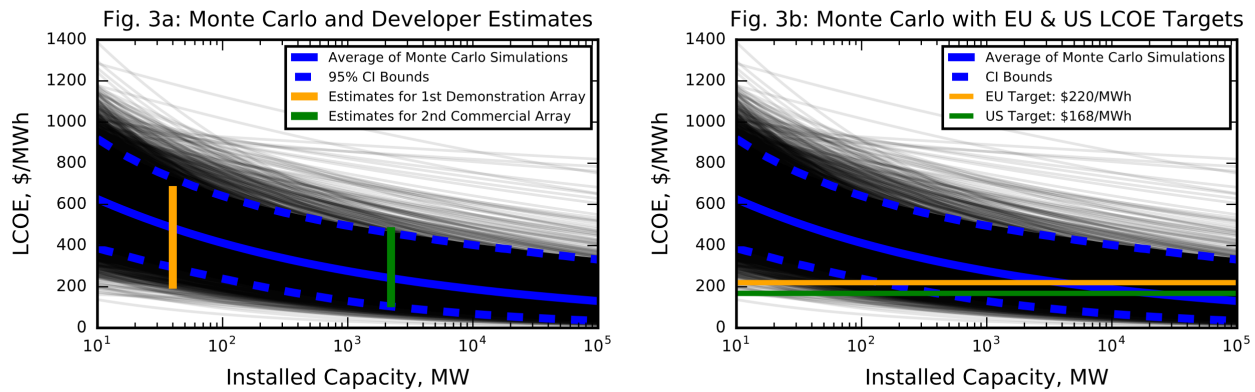


Figure 3: Monte Carlo results with (a) developer estimates [18] and (b) LCOE targets [15], [17].

### 3.2 Levelized Cost of Electricity Timeline

The deployment rate of wave technologies will determine whether the LCOE targets could be reached by 2025 and 2030, respectively. Applying the 38.1% CAGR of offshore wind to an initial installed wave energy capacity of 4.4 MW in 2016 [15] yields the LCOE curves shown in Fig. 4. Based on the two-stage Monte Carlo simulation, the probability of meeting or exceeding the European and U.S. LCOE goals by the targeted dates is 1.2% and 3%, respectively. While meeting these goals is statistically unlikely under the assumptions used in this paper, innovation programs can dramatically accelerate the deployment of wave technologies. Following the Carbon Trust's deployment model [20], the two-stage Monte Carlo simulation results in the probability of meeting or exceeding the European and U.S. LCOE targets to be 33% and 28%, respectively.

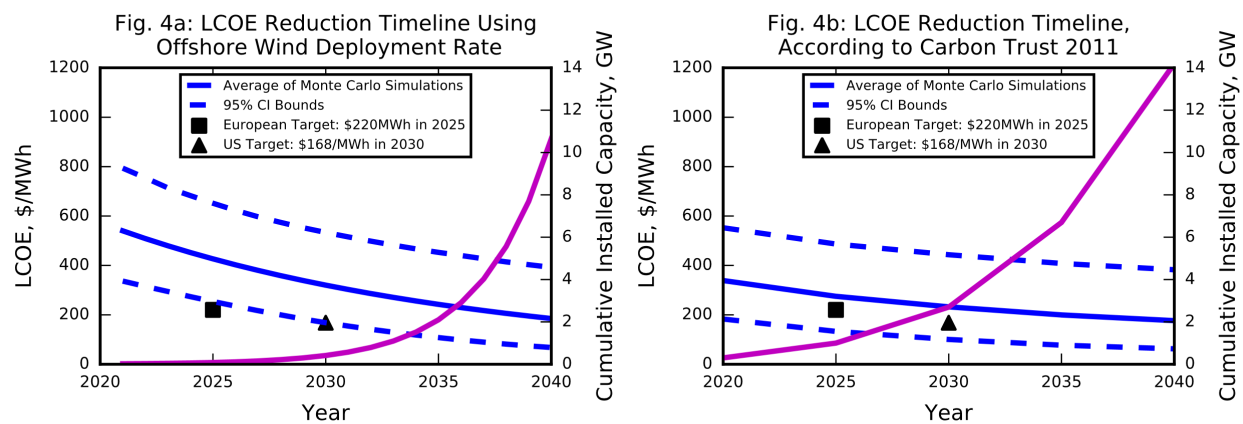


Figure 4: Wave energy LCOE (blue) and cumulative installed capacity (purple) over time using deployment and learning rates from (a) offshore wind [14], [22] (b) the Carbon Trust [20].

#### 4. Conclusions and Policy Implications

The two-stage Monte Carlo model used to simulate variability in both the current estimates of the LCOE and the expected one-factor learning rate for wave energy technologies agree with the results projected by wave energy developers. However, when a deployment rate comparable to the CAGR of offshore wind is used to forecast wave energy deployment, the LCOE reduction targets of the European Union and U.S. Department of Energy pose a challenge, with the probability of reaching or exceeding these targets being 0.9% and 2.5%, respectively. However, with substantial research, development, and deployment funding coupled with supporting policies, the learning rate could be increased significantly. Applying an accelerated learning rate suggested by the Carbon Trust, the probability of reaching or exceeding these targets would be 30% and 25%, respectively. This demonstrates the criticality of support mechanisms to achieve learning rates that achieve government targets and lead to economic competitiveness in the utility-scale markets.

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