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MINIMIZING COST IN A 100% RENEWABLE ELECTRICITY GRID: A CASE STUDY OF WAVE ENERGY IN CALIFORNIA

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ABSTRACT

Wave energy converters have yet to reach broad market viability. Traditionally, levelized cost of energy has been considered the ultimate stage gate through which wave energy developers must pass in order to find success (i.e., the levelized cost of wave energy must be less than that of solar and wind). However, real world energy decisions are not based solely on levelized cost of energy. In this study, we consider the energy mix in California in the year 2045, upon which the state plans to achieve zero carbon energy production. By considering temporal electricity production and consumption, we are able to perform a more informed analysis of the decision process to address this challenge. The results show that, due to high level of ocean wave energy in the winter months, wave energy provides a valuable complement to solar and wind, which have higher production in the summer. Thus, based on this complementary temporal aspect, wave energy appears cost-effective, even when the cost of installation and maintenance is twice that of solar and wind.

NOMENCLATURE

EIA Energy Information Administration
LACE levelized avoided cost of energy
LCOE levelized cost of energy
LCOS levelized cost of storage
RPS renewable portfolio standard
WEC wave energy converter
$J_i(t)$ monthly generation for source i
g_i additional generation capacity for source i
c_i cost of g_i
$r_i(t)$ monthly renewable resource for source i
γ_i average capacity factor for source i

INTRODUCTION

To-date, a large majority of the techno-economic assessments on wave energy have focused on levelized cost of energy (LCOE). A reduction in LCOE below or near that of other competing energy generation technologies, such as natural gas, solar and wind, is often held as *the* key barrier for the success of wave energy converters (WECs). However, LCOE is not a perfect measure of market viability for an energy generation asset.

The US Energy Information Administration (EIA) directly warns against using LCOE as the sole measure for comparing energy generation technologies ("LCOE does not capture all of the factors that contribute to actual investment decisions, making the direct comparison of LCOE across technologies problematic and misleading as a method to assess the economic competitiveness of various generation alternatives" [1]), and instead recommends that LCOE be used along with additional metrics such as levelized avoided cost of energy (LACE) and levelized cost of storage (LCOS). While LCOE looks directly at the cost of a potential generator asset by taking the ratio of costs, including capital, financing, operations, and maintenance costs, against the amount of energy produced by the asset of its lifetime, LACE helps capture the relative value of one generation option against available alternatives.

In this brief study, we build off recent efforts [2, 3] to consider a LACE analysis for the state of California, with a focus towards understanding market viability of WECs. California is a particularly interesting location for such an analysis because of its renewable energy portfolio standard (RPS), which requires utilities to have 60% retail electricity delivered by renewable sources by 2030 and 100% by 2045.[1] Thus, we consider the problem of eliminating the fossil fuel based generation sources from the grid. We quantify the amount of power generation capacity that must be displaced by 2045, and use this to perform a LACE-style analysis considering the relative cost of fulfilling the energy deficit with WECs, wind turbines, and solar photovoltaic panels.

LITERATURE REVIEW

Wave energy is an untapped renewable energy resource, that to date has been under-utilized, in part due to its high resource dependence and operational "complexity." To achieve grid penetration, WECs must not to only survive amongst the harshest resources (i.e., large loadings from waves, corrosion from salt concentration, etc.), but must also produce power at comparable levels to other more mature renewables (e.g., solar and wind). While the challenge is substantial, the wave energy resource is amongst the most dense and predictable resources [4, 5]. To understand the intricacies of WECs, several studies have discussed the challenges scaling deployments [6, 7, 8, 9].

Numerous studies have considered integration of wave energy into energy systems and found that it provides grid stability and can reduce the cost of energy storage $\sim$40-60% [10, 11, 12, 13, 14, 15]. This can also lead to huge benefits, as the current costs for energy storage systems, when located "behind the meter," can run up as high as 485-1000 $/MWh (as standalone solutions), 223-384 $/MWh as part of storing electricity by photovoltaics for industrial applications, and 457-663 $/MWh for residential solutions [16]. Coastal regions may also see benefits in terms of reduced usage of existing transmission lines and a reduction of single point failures [14]. For wave energy, the reported LCOE values have a range of 80-600 $/MWh underlying the uncertainties which are dependent on WEC archetype, resource, installed capacity, and other assumptions [17, 18, 19, 20].

[1]For a listing of RPSs within the United States, see, e.g., `https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx`.

A LACE ANALYSIS IN CALIFORNIA

A typical LACE analysis is driven by the marginal generation price along with capacity payments.

$$LACE = (\text{marginal generation payment}) + (\text{capacity payment}) \tag{1}$$

If one is considering a LACE analysis for present-day, it is possible to obtain a good estimate via (1). However, it is a fundamental point our 2045 analysis that the cost/value of energy will be dramatically changed by the need to remove carbon producing generation assets. Thus, we must pursue a different approach.

First, we consider the current status of electricity production in California. Next, we use this information to execute two types of analyses to predict ways in which the deficit created by removing carbon producing generation assets from the grid can be dealt with. An explicit approach is first used to consider the additional solar/wind generation that would be needed. A constrained optimization approached is then used to solve for the least expensive means of adding renewable generation capacity to meet California's RPS.

Before proceeding further, it is necessary to state a set of assumptions on which the analyses performed within this study will be based. Firstly, we consider a finite set of renewable energy technologies that may be built. While both hydroelectric dams and nuclear power plants have many attractive qualities as dispatchable based loads, both are limited in their application due to social/political limitations. Therefore, we consider only solar, wind, and wave energy in our analyses. In this study, we consider the monthly average electricity generation and demand. While shorter times-scales are indeed important and should be considered in subsequent studies, a monthly analysis can provide useful insights. Storage has the effect of smoothing the power generation or demand profile. Most large-scale energy storage technologies are not well-suited to storing energy over the timescale of months; pumped hydro and compressed air storage are likely the most viable solutions (see, e.g., [21]). Thus, we do not consider storage in this paper. Another consideration is grid expansion, but the obvious limitation of this option is the large capital cost and socio-political challenges.

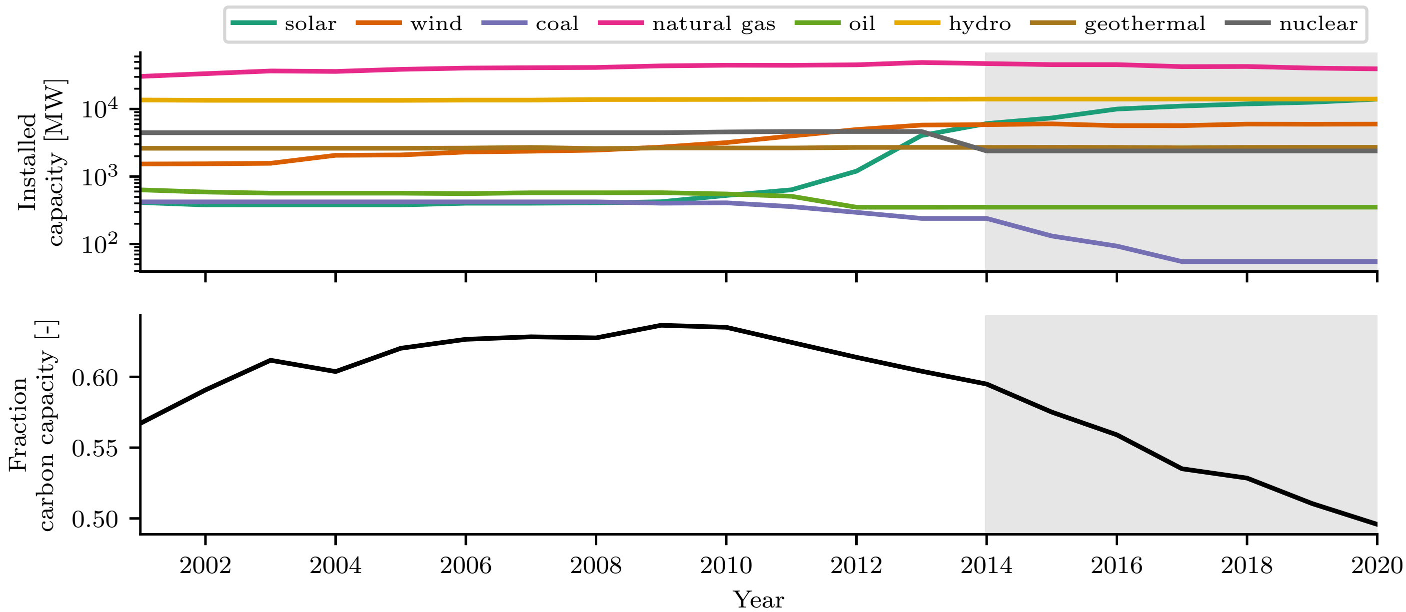

FIGURE 1. ELECTRICITY GENERATION CAPACITY OVER TIME IN CALIFORNIA, SOURCE: EIA. GREY SHADED AREA SHOWS PERIOD OF 2014-2020 CONSIDERED FOR THIS STUDY.

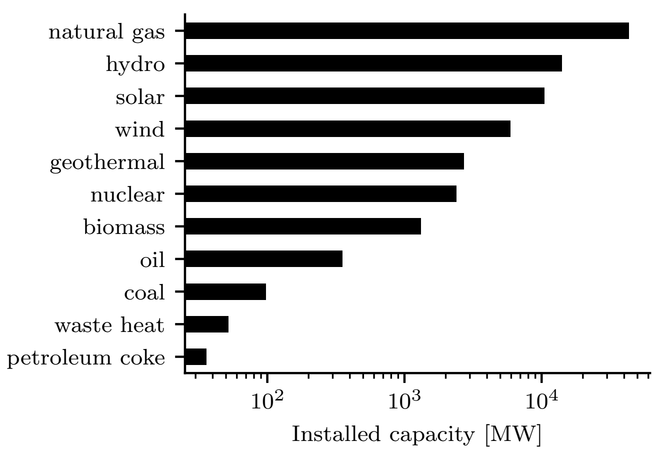

FIGURE 2. MEAN CALIFORNIA GENERATION CAPACITY BY SOURCE (2014-2020), SOURCE: EIA.

Current status

Figure 1 shows the electricity generation by source in California for the period of 2001-2020. In an attempt to use data from a period over which changes in the electricity grid were less dramatic, in this study we will consider data from 2014-2020, which is highlighted in gray in Figure 1. The average power production for each source during the 2014-2020 period is shown in Figure 2. We can see that natural gas is the largest generation source in California during this period, followed by hydroelectric dams and utility-scale solar.

Of particular interest in this study are the installed capacities of all fossil fuel generation assets (coal, natural gas, and oil), solar, and wind; these are shown in Table 1. Additionally, Table 1 shows the average capacity factors for each of these generation types. These capacity factor values computed directly from the data used in this study are in line with those reported elsewhere in literature [1, 22].

We see that the installed capacity of fossil fuel type generators is three times greater than that of solar and wind combined. Additionally, the capacity factor of the fossil fuel generators is much higher than that of solar and wind. Thus, for 1 GW of capacity, the yearly output of a fossil fuel plant will (on average), be 0.77 GW whereas the output of similarly rated solar array or wind turbine farm will be closer to 0.25 GW. Along with the bulk

TABLE 1. AVERAGE INSTALLED CAPACITIES AND CAPACITY FACTORS 2014-2020, SOURCE: EIA.

	Capacity [GW]	Capacity factor [-]
fossil	43.74	0.77
solar	10.44	0.24
wind	5.88	0.26

capacity factor, one must also consider temporal variation ("intermittency") in electricity production from various sources.

Monthly electricity balance

Electricity is a heterogeneous good [23, 24, 25], in that 1 kWh of electricity generated in November in Texas is not exchangeable for 1 kWh of electricity generated in California in May. For our present study, we will focus on the temporal aspect of this heterogeneous nature. The upper-most axes in Figure 3 show the average monthly electricity generation for fossil (coal, natural gas, and oil), solar, wind, and wave (which is zero). Solar and wind generation peak in the summer months, whereas fossil generation is an order of magnitude larger and peaks in the fall/winter.

This data may be distilled to consider what percentage of the total monthly electrical generation comes from fossil sources (second axes in Figure 3). In May, only 35% of California's electrical generation is derived from fossil sources, but in December the level is 58%.

Taking this logic one step further, we may determine how many times more solar/wind generation would need to be added to offset that electricity produced by fossil sources. If the demand for electricity is considered to be similar in 2045,[2] this problem can be considered in terms of offsetting the deficit created by removing the fossil based generation from the grid. If $J_f(t)$, $J_s(t)$, and $J_w(t)$ are the monthly fossil, solar, and wind production, respectively, we may find

$$\alpha(t) = \frac{J_f(t)}{J_w(t) + J_s(t)}, \tag{2}$$

where $\alpha(t)$ is the monthly multiplier of new solar/wind generation capacity. The results of (2) are shown in the third set of axes in Figure 3. In May, one must only add 136% to the existing solar panels and wind turbines to offset the fossil generation. However, to maintain a positive energy balance in December would require an additional 485% of the existing solar/wind generation capacity.

As a final step in this analysis, we may infer the resource for solar and wind in California by normalizing the monthly production levels (lowest axes in Figure 3). Additionally, based on hindcast data, we can include the wave energy resource contribution [26]. From the lowest axes in Figure 3, it is immediately clear that the wave energy resource in California is complementary to solar and wind (which have very similar resource curves).

[2] Recent trends indicate that electricity demand in California is neither growing nor decreasing.

Constrained optimization problems

The previous analysis was able to give a solution in terms of a simple factor of the existing solar and wind generation capacity, but the best solution may involve some arbitrary mixture of additional capacity. To solve for this optimal mixture, a constrained optimization problem can be formulated.

$$\min_{g} \left(\sum_i g_i \cdot c_i \right) \tag{3a}$$

$$\text{s.t.} \quad \sum_i r_i(t) \cdot \gamma_i \cdot g_i \geq J_f(t) \tag{3b}$$

Here, g_i and c_i are additional renewable generation capacity and the cost of that capacity for source $i \in$ (solar, wave, wind). Thus, objective function (3a) represents the total cost of additional renewable generation. The normalized monthly resource for each technology (solar, wind, and wave) is $r_i(t)$ and the average capacity factor is γ_i. The monthly energy deficit created by the removal of fossil generation assets is $J_f(t)$. We constrain the solution of the problem with (3b) such that the monthly net energy balance is positive. In practice, (3) was solved via a sequential least squares programming algorithm.

We use (3) to conduct two case studies. First, we examine the scenario where wind and solar generation capacity can be added to satisfy (3). Next, we consider (3) with wave energy generation capacity.

Case study I: solar/wind As reported by [22], the price of onshore US wind turbine installations is on the order of 1000 \$/kW of nameplate capacity. According to the EIA Annual Energy Outlook 2020 [1], the capital costs of solar and onshore wind and solar are, respectively, 1331 and 1319 \$/kW of nameplate capacity. Note that these values represent the installation cost, but do not include other important costs such as operations and maintenance ("O&M"). Since the costs are similar, we will consider them as equal initially ($c_s = c_w$).

Applying (3) gives the optimal solution illustrated in Figure 4. Here, we see the initial deficit created by removing fossil generation assets, which is effectively the initial condition for our optimization problem if $g_s = g_w = 0$. The optimal solution shown in Figure 4 ensures that demand for electricity is met each month while minimizing costs. We can see that in November and December the optimal solution results in a monthly electricity balance that is close to zero, but positive. This result aligns with that seen using (2) and illustrated in the third set of axes in Figure 3.

In this case, in which the cost of solar and wind are taken to be equal, the optimal solution is to use wind to meet the unmet electrical demand. This is likely due to the mean capacity factor

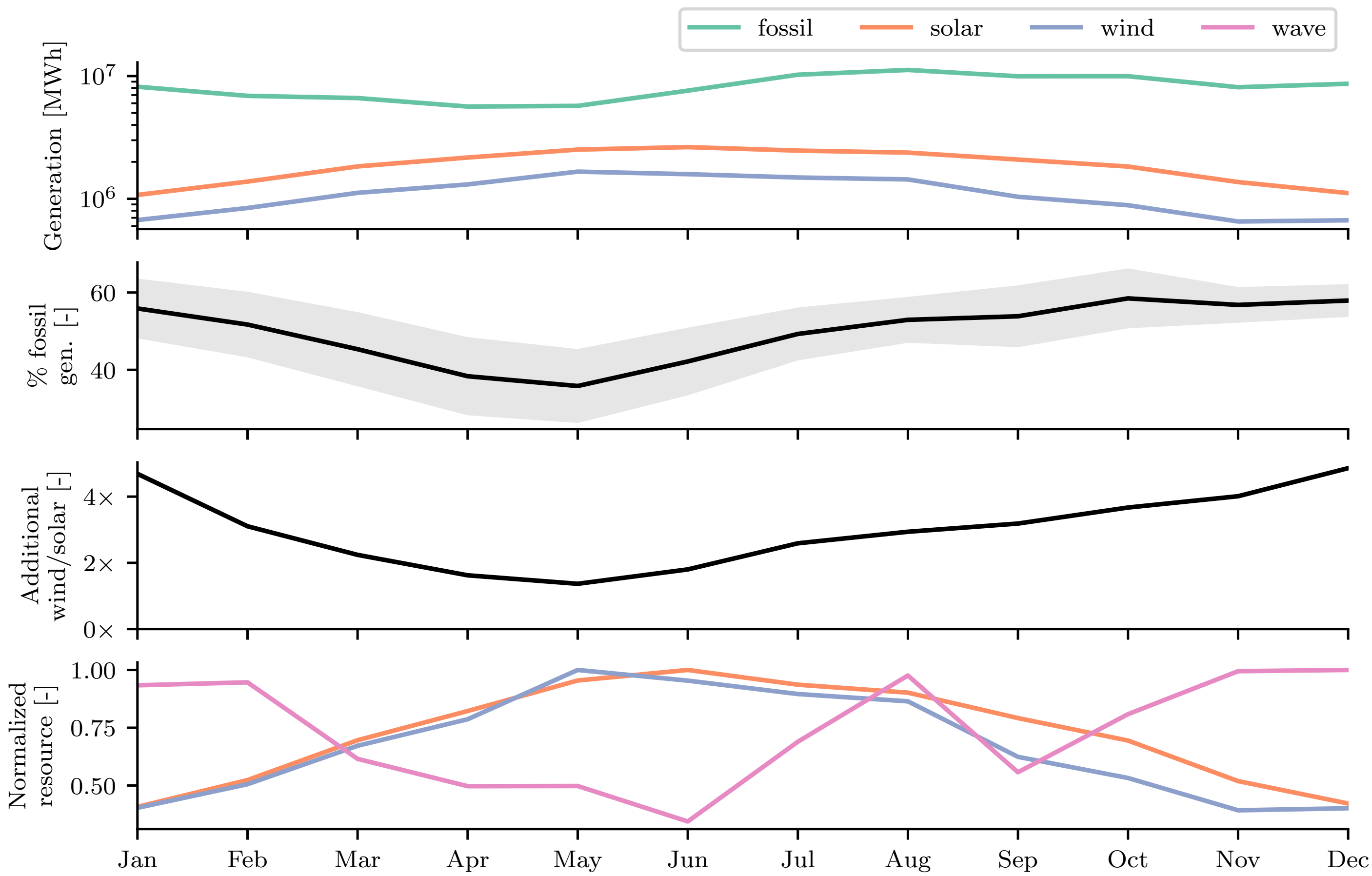

FIGURE 3. MEAN CALIFORNIA FOSSIL (COAL, NATURAL GAS, OIL), SOLAR, AND WIND GENERATION (2014-2020), ALONG WITH ADDITIONAL FACTOR OF EXISTING WIND/SOLAR NEEDED TO DISPLACE FOSSIL GENERATION SOURCES. NORMALIZED RESOURCE CURVES FOR SOLAR AND WIND TAKEN BASED ON PREVIOUS GENERATION, WAVE RESOURCE CURVE TAKE FROM HINDCAST DATA.

of wind (0.258) being slightly greater than that of solar (0.240). If we consider a case where the cost of solar is slightly less than that of wind ($c_s = 0.9c_w$), the optimal solution uses only additional solar capacity.

It is interesting to note that the optimal solution uses a mixture of both solar and wind for only a narrow range of relative costs ($0.9061 < c_s/c_w < 0.9079$). In other words, the solution is very sensitive to the relative costs of these two generation types, likely because their resource curves (lowest axes in Figure 3) are so similar. Note again that, while this analysis looks only at monthly electricity production/demand, smaller time-scales may also be important (e.g., diurnal variation in both solar irradiance and wind).

Case study II: solar/wind/wave Finally, we may apply (3) to study the potential penetration of wave energy generation assets. We consider a range of wave energy costs and average capacity factor values as no reliable data is available for the cost or intermittency of wave energy. Thus, we consider (3) for a range of wave energy cost and average capacity factor values.

The results of this analysis are shown in Figure 5. The relative utilization of each generation type is shown for wave energy costs ranging from one tenth that of solar and wind to ten times that of solar and wind. The different sets of axes in Figure 5 show the results of this analysis for different average capacity factors for wave energy (0.25, 0.50, 0.75).

As expected, when the cost of wave energy is very low, WECs compose the entire optimal solution. Conversely, if the cost of wave energy is very high, the optimal solution relies entirely on new wind turbines as seen in Case-study I. However, if the capacity factor of wave energy is on par with solar and wind (0.25: the upper-most axes in Figure 5), WECs provide 20% of

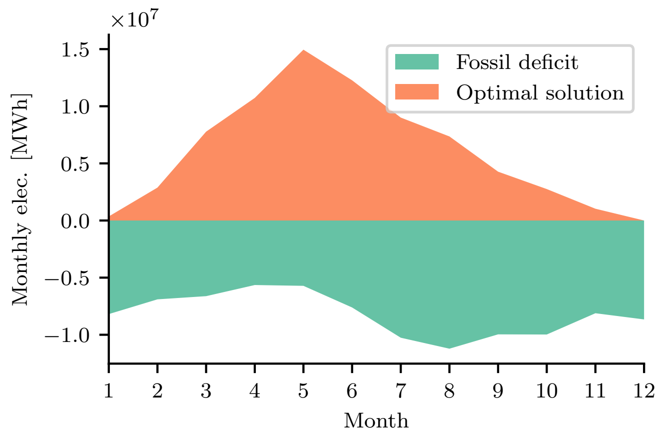

FIGURE 4. CASE-STUDY I: INITIAL DEFICIT DUE TO REMOVAL OF FOSSIL GENERATION AND OPTIMAL SOLUTION FOR MEETING ELECTRICITY DEMAND WITH SOLAR/WIND.

the optimal solution even when they cost twice as much as solar and wind. This is due to the complementary nature of the wave energy resource curve with respect to that of solar and wind. If the capacity factor of wave energy is higher, which may indeed be possible given the nature of ocean waves [2], wave energy can be viable with even higher costs – at a capacity factor of 0.75, wave energy still contributes 10% of the optimal solution when the cost is 5× that of solar and wind.

CONCLUSION

In this study, we analyzed the decision process for meeting California's 2045 renewable portfolio standard to completely eliminate fossil fuel based electricity generation. Via a constrained optimization problem, we find that even when the costs of wave energy are higher than that of wind or solar, it may be a cost effective solution. This is due to the fact that while wind and solar have their highest output in California in the summer months, wave energy has the highest output in the winter.

This study considered only monthly electricity demand/production, but future analyses should consider smaller smaller time-scales (e.g., hourly). Additionally, it may be possible to include the effects of energy storage in the optimization problem and to reflect other value/cost considerations, such as integration costs. Furthermore, it may be possible to consider the output of specific WEC devices and/or device types to provide more detailed results.

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REFERENCES

[1] U.S. Energy Information Administration (EIA), 2020. Annual Energy Outlook 2020. Tech. Rep. AEO2020, U.S. Energy Information Administration, Washington, DC, January.

[2] Coe, R. G., Ahn, S., Neary, V. S., Kobos, P. H., and Bacelli, G., 2021. "Maybe less is more: Considering capacity factor, saturation, variability, and filtering effects of wave energy devices". *Applied Energy,* ***291***, p. 116763.

[3] Lavidas, G., and Blok, K., 2021. "Shifting wave energy perceptions: The case for wave energy converter (WEC) feasibility at milder resources". *Renewable Energy,* ***170***, pp. 1143–1155.

[4] Reguero, B., Losada, I., and Méndez, F., 2015. "A global wave power resource and its seasonal, interannual and long-term variability". *Applied Energy,* ***148***, pp. 366–380.

[5] Sasaki, W., 2017. "Predictability of global offshore wind and wave power". *International Journal of Marine Energy,* ***17***, pp. 98–109.

[6] Magagna, D., and Soede, M., 2019. Low Carbon Energy Observatory: Ocean Energy Technology Development Report 2. Tech. rep., Joint Research Centre (JRC), Luxembourg: Publications Office of the European Union.

[7] Babarit, A., Bull, D., Dykes, K., Malins, R., Nielsen, K., Costello, R., Roberts, J., Bittencourt Ferreira, C., Kennedy, B., and Weber, J., 2017. "Stakeholder requirements for commercially successful wave energy converter farms". *Renewable Energy,* ***113***, pp. 742–755.

[8] Babarit, A., 2015. "A database of capture width ratio of wave energy converters". *Renewable Energy,* ***80***, pp. 610–628.

[9] Lavidas, G., 2019. "Developments of energy in EU – unlocking the wave energy potential". *International Journal of Sustainable Energy,* ***38***(3), pp. 208–226.

[10] Keiner, D., Salcedo-Puerto, O., Immonen, E., van Sark, W. G., Nizam, Y., Shadiya, F., Duval, J., Delahaye, T., Gulagi, A., and Breyer, C., 2022. "Powering an island energy system by offshore floating technologies towards 100% re-

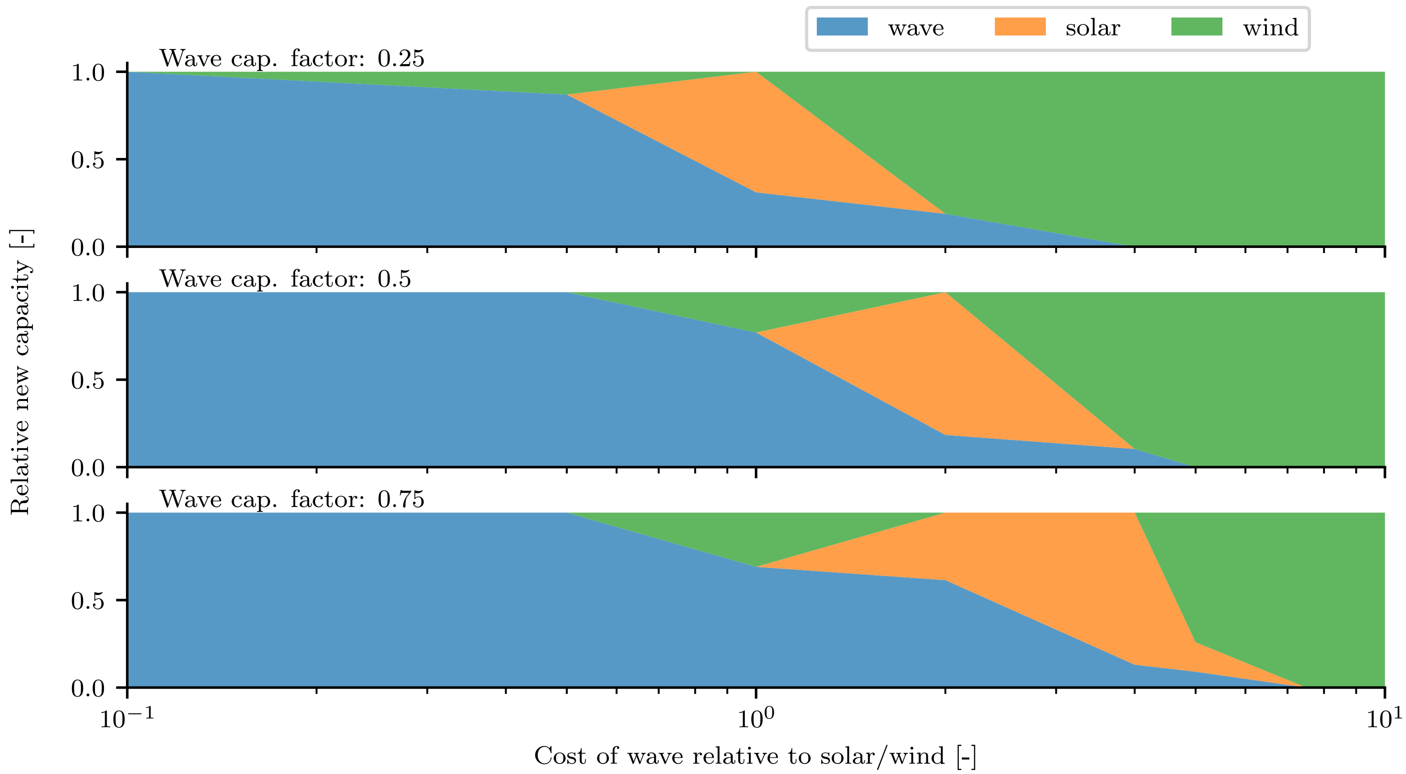

FIGURE 5. CASE-STUDY II: RELATIVE UTILIZATION OF ADDITIONAL GENERATION ASSETS FOR A RANGE OF RELATIVE COSTS OF WAVE ENERGY. RESULTS SHOWN FOR DIFFERENT MEAN WAVE ENERGY CAPACITY FACTORS (0.25, 0.50, 0.75).

newables: A case for the Maldives". *Applied Energy*, ***308***, p. 118360.

[11] Friedrich, D., and Lavidas, G., 2017. "Evaluation of the effect of flexible demand and wave energy converters on the design of hybrid energy systems". *Renewable Power Generation*, ***12***(7).

[12] Lund, H., 2006. "Large-scale integration of optimal combinations of pv, wind and wave power into the electricity supply". *Renewable Energy*, ***31***(4), pp. 503–515.

[13] Stoutenburg, E. D., Jenkins, N., and Jacobson, M. Z., 2010. "Power output variations of co-located offshore wind turbines and wave energy converters in California". *Renewable Energy*, ***35***(12), pp. 2781–2791.

[14] Bhatnagar, D., Bhattacharya, S., Preziuso, D. C., Hanif, S., O'Neil, R. S., Alam, M. J. E., Chalishazar, V. H., Newman, S. F., Lessick, J. D., Garcia Medina, G., Douville, T. C., Robertson, B., Busch, J., Kilcher, L., and Yu, Y.-H., 2021. Grid value proposition of marine energy. Tech. Rep. PNNL-31123, Pacific Northwest National Lab. (PNNL), Richland, WA (United States), 11.

[15] de Andres, A., MacGillivray, A., Roberts, O., Guanche, R., and Jeffrey, H., 2017. "Beyond LCOE: A study of ocean energy technology development and deployment attractiveness". *Sustainable Energy Technologies and Assessments*, ***19***, pp. 1 – 16.

[16] Lazard, 2019. Levelized Cost of Storage. Tech. rep., Lazard.

[17] MacGillivray, A., Jeffrey, H., Winskel, M., and Bryden, I., 2014. "Innovation and cost reduction for marine renewable energy: A learning investment sensitivity analysis". *Technological Forecasting and Social Change*, ***87***, pp. 108–124.

[18] Magagna, D., Monfardini, R., and Uihlein, A., 2016. JRC Ocean Energy Status Report. Tech. rep.

[19] Soukissian, T., Denaxa, D., Karathanasi, F., Prospathopoulos, A., Sarantakos, K., Iona, A., Georgantas, K., and Mavrakos, S., 2017. "Marine Renewable Energy in the Mediterranean Sea: Status and Perspectives". *Energies*, ***10***(10), p. 1512.

[20] Lavidas, G., and Blok, K., 2021. "Levelised Cost of Electricity for wave energy converters and the perception of milder resource non-viability in the North Sea". In 11th European Wave and Tidal Energy Conference (EWTEC), 11th European Wave and Tidal Energy Conference (EWTEC),

pp. 1–7.
[21] Aneke, M., and Wang, M., 2016. “Energy storage technologies and real life applications – a state of the art review”. *Applied Energy,* ***179***, pp. 350 – 377.
[22] Wiser, R. H., and Bolinger, M., 2019. 2018 Wind Technologies Market Report. Tech. rep., U.S. Department of Energy (DOE) Wind Energy Technologies Office, 08.
[23] Joskow, P. L., 2011. “Comparing the costs of intermittent and dispatchable electricity generating technologies”. *American Economic Review,* ***101***(3), May, pp. 238–41.
[24] Hirth, L., 2013. “The market value of variable renewables: The effect of solar wind power variability on their relative price”. *Energy economics,* ***38***, pp. 218–236.
[25] Ueckerdt, F., Hirth, L., Luderer, G., and Edenhofer, O., 2013. “System LCOE: What are the costs of variable renewables?”. *Energy,* ***63***, pp. 61 – 75.
[26] Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., and Thépaut, J.-N., 2018. ERA5 hourly data on single levels from 1979 to present.