Pre-print, to appear in IET Renewable Power Generation, 2019

IET Renewable Power Generation

Brief Paper

ISSN 1751-8644
doi: 0000000000
www.ietdl.org

Estimating the Impact of Ocean Wave Energy on Power System Reliability with a Well-Being Approach

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Abstract: Ocean wave energy is a developing industry that provides many attractive qualities for utilities to meet future energy demand. Therefore, it is important to investigate and understand the impact that ocean wave energy has on power system reliability. Reliability assessment techniques have been applied to systems with variable amounts of wind penetration, but as of yet, no study has explored the impacts that ocean wave energy may have on the reliability of power grids. Our approach to this problem applies a sequential Monte Carlo (MC) technique coupled with a Well-Being analysis approach to capture the seasonal variations associated with the ocean and then calculate key loss-of-load indices. We benchmark this method on the IEEE Reliability Test System 1996 (RTS-96) and integrate synthesized ocean wave energy farms throughout the system. Our results suggest that wave energy results in a small decrease on the reliability of the power system, however this change does not result in additional failure states as compared to the base system. Additionally, we are able to mitigate marginal system states with a relatively small increase in system capacity.

1 Introduction

Integration of renewable energy has been a topic of great discourse as the public view changes about our dependence on fossil fuels. As a result of this, and decreasing costs, renewable resources are being installed around the globe at an unprecedented rate [1]. This increasingly widespread adoption does not go unbounded as there are several challenges and limitations that need to be overcome, of which the most commonly discussed is resource variability [2]. The shift from fossil fuels now means that our energy supply is weather dependent. In March of 2015, Germany experienced a solar eclipse which created a need of 10 GW to be ramped over the course of a just a few hours [3]. Problems such as these suggest that it is necessary to conduct comprehensive grid integration studies with modern models that incorporate the inherent variability associated with renewable energy.

Ocean wave energy is a relatively new energy source with potential to satisfy much of our modern power demand. Since the wave industries inception in the 1970s, researchers at the Pacific Marine Energy Center have focused their efforts on device design, energy characterization, and environmental impact among other things [4]. As a result, studies into how wave energy devices will interact with the local energy infrastructure are very limited. Early in 2010, authors O'Sullivan *et. al.* [5] examined technical, economic, and regulatory challenges of developing a grid interconnected wave energy farm. The results of their efforts was a cost model which indicated that a 20 MW wave farm facility would cost approximately €19 million. Authors M. Santos *et. al.* [6] produced several case studies which looked into various technical aspects of the grid integration of marine and tidal energy. Such as, dynamic modeling, load flow analysis, voltage stability, and rotor angle stability to name a few. More recently in 2019, however, researchers in [7] have completed an extensive investigation to the current limiting factors of the wave energy technology. They suggest that, although the technology is not currently cost competitive, advances in design and relaxation of grid codes would change this. In a more technical assessment, references [8, 9] studied power quality issues, such as voltage limits, flicker, low voltage ride through, and potential harmonic injections from power electronics. In [10], a wave-to-wire model was created and control strategies were developed to mitigate WECs impact to the point of common coupling. To the best of the authors knowledge, however, there are no studies that examine the impact wave energy has on power system reliability.

Power system reliability is, in essence, the requirement for the grid to meet both the generation and transmission capacity needs of its customers. As many grid planners know, having a variable resource limits their ability to do so. To mitigate these issues, the system operators who manage the grid require that all wind plants manage accurate wind real-time and day-ahead forecasts. Therefore, any reliability assessment of renewable energy sources need to be assessed in a sequential fashion. That is, account for time changes in generation capacity. To address this and the research gap in current wave energy trends, this paper will use the system Well-Being analysis [11–15] coupled with a sequential Monte Carlo (MC) method of system state generation. As an extension to traditional reliability methods, the Well-Being Analysis categorizes each operating system state–as generated by the sequential MC method–as either being *healthy*, *marginal*, or *at-risk*. Further, the system Well-Being Analysis incorporates a deterministic criteria into the probabilistic assessment. In doing so, this step allows system planners to incorporate personal experience into the reliability assessment. In this paper, for instance, we use the loss of the largest online generator, which has been adopted in several studies [15, 16], to assess the contingency reserve of the power system.

Over the years, the Well-Being framework has seen success in successfully assessing the reliability impact of several renewable energy sources. For example, References [17, 18] applied a auto-regressive moving average (ARMA) model to develop the wind-speed power curves used for their MC analysis. A similar approach was used in Reference [15] but instead proposes an alternative to the MC method by computing the capacity outage probability table (COPT), i.e., a discretized probability distribution function for generation capacity. In addition to wind modeling, researchers Atwa *et. al.* [19] modelled an hourly clearness index to compute the solar irradiance and solar photovoltaic production. The key observation to make from this literature is that the accuracy of the assessment lies in the level of detail in the renewable energy model.

With this in mind, the main contribution this paper provides is to quantify the impact, if any, that utility scale ocean wave energy devices have on the transmission system's ability to deliver reliable power. To this end, we leverage mathematical models for WEC devices developed in [20]. While this is elaborated upon in Section 3, this methodology leverages data from a network of meteorological and oceanographic sensors–called the National Data Buoy Center (NDBC) [21]–to generate a wave power time-series at sub-hourly intervals. This time-series is then used to build probabilistic models for the reliability assessment (Well-Being Analysis) of the power system. In addition to estimating any potential benefit and/or risk to reliability, we examine how much additional grid support is necessary to successfully integrate wave energy.

2 Power System Reliability

Power system reliability refers to the ability of the power system to deliver expected service through both planned and unplanned events. This definition implicitly means that the power system will: 1) have enough generation and transmission capacity to meet peak demand, 2) maintain a steady system voltage and frequency, and 3) contains adequate flexibility to handle random load and generation variations. This last characteristic highlights the major issue in that the assessment of power system reliability requires probabilistic methods and tools. Typically, these methods take an analytical or numerical approach to solve the reliability problem.

The analytical method involves creating a state representation, most commonly using Markov models, and solving using a recursive and iterative process [22]. Analytical methods, however, become computationally burdensome as the size of the power system and number of random variables included in the analysis increases. Furthermore, a state based approach cannot be directly applied to system with renewable energy. For example, developing a Markov model which accounts for random weather changes will be complex and have many assumptions. This, however, has not stopped researchers as Reference [23] has shown it is possible to accurately develop a state based model for large wind system.

Numerical approaches to power system reliability often take the form of MC methods. Literature has suggested that when the power system is complex—as is typical in medium to large power systems—a MC approach simplifies the reliability problem at the cost of added computational complexity [24]. MC methods are classified as either non-sequential or sequential. In the former, states for each component are sampled, and each system state is considered independent from each other. Conversely, sequential sampling techniques capture the chronological operation cycles of each component and the system as a whole. In both non-sequential and sequential techniques, the status of each system component is sampled based on a uniformly distributed random number $U[0, 1]$.

In the non-sequential MC method, component and system states are calculated using

$$S_i = \begin{cases} \text{Online}, & \text{if } U_i \geq \text{FOR}_i \\ \text{Offline}, & \text{if } U_i < \text{FOR}_i \end{cases} \tag{1}$$

and

$$\text{FOR}_i = \frac{\text{MTTR}_i}{\text{MTTR}_i + \text{MTTF}_i} \tag{2}$$

where S_i, FOR_i, MTTR_i, and MTTF_i are the state, Forced Outage Rate (FOR), Mean Time to Repair (MTTR), and Mean Time to Fail (MTTF) of the ith system component, respectively. The above process is then performed for n system components with the assumption that each element is independent from each other. The important characteristic here is that we are more interested in whether or not a component is online or offline. Conversely, sequential MC methods consider the chronological operating cycles of each system component. Given the MTTR and MTTF for each component, the systems operating cycle can be determined by

$$\text{TTF}_i = -\text{MTTF}_i * \ln U_i \tag{3}$$

$$\text{TTR}_i = -\text{MTTR}_i * \ln U_i \tag{4}$$

where TTR_i and TTF_i is the Time to Repair (TTR) and Time to Fail (TTF) for the ith component.

In both methods, we are interested in approximating an *indicator* which quantifies the power systems reliability. For example, the Loss of Load Probability (LOLP) Loss of Load Duration (LOLD), Loss of Load Frequency (LOLF), and the Expected Energy Not Supplied (EENS) are all appropriate indicators for reliability. As with all approximation methods convergence of the indicator is important. In MC methods it is common to use the *Coefficient of Variation*—a measure of an indicators dispersion around its mean—as the MC stopping criteria. The coefficient of variation is defined as

$$\alpha = \frac{\sigma(x)}{E(x)} \tag{5}$$

where x is the estimated value of the index, $E(x)$ is the expectation of the system index, and σ is the standard deviation of the estimated expectation of the system index. Once the coefficient of variation falls below some tolerance ε, simulations will stop. How quickly the stopping criteria converges depends on which index is chosen. Earlier works have determined that the Loss of Energy Expectation (LOLE) converges at the slowest rate and should be used to guarantee that all other indices are accurate [25].

3 Wave Power Modeling

3.1 Background of Ocean Wave Energy

Ocean waves are generated by the wind blowing along the surface of the water. The wind's speed, duration, and fetch all impact the size of the ocean waves. We know that for latitudes between 30°-60° waves are bigger on the US West Coast than those on the US East Coast due to the prevailing westerly winds. For example, the total ocean energy available is 590 TWh/y and 240 TWh/y, respectively [26]. By comparison, the total U.S. energy demand for 2012 was approximately 4,000 TWh [27]. This suggests that wave energy alone could satisfy 10-15% of our electricity needs. This, however, is the best case scenario which doesn't take into consideration efficiency and transmission losses.

Ocean wave energy has some unique qualities that distinguish itself from wind and solar energy. First, ocean wave energy has very low hour-to-hour variability [28]. The seasonal dependence of ocean energy is generally favorable because power production traditionally peaks in the winter months when electrical demand is high. Energy density for the ocean in the Pacific Northwest region is on average 30 kW/mcl [26]. By comparison, wind and solar densities are around 0.5 kW/m^2 and 1 kW/m^2, respectively [29]. Additionally, ocean wave energy benefits from being close to highly populated areas in the case of the United States of America, which significantly reduces the need for long high-voltage transmission lines.

3.2 Ocean Energy Power Takeoff

Power takeoff (PTO) is the term used to describe the power transferred from a mechanical system to an electrical system. Modeling this interaction–and the underlying physics–is the first step to assess the potential power output from a WEC device. From [31], we write the linear equations of motion for a floating body as follows

$$m\ddot{X} = F_e + F_r + F_h + F_{\text{PTO}} \tag{6}$$

where $\ddot{X}$ is the acceleration vector in all 6 degrees of freedom (as shown in Fig. (1)), F_e is the wave excitation force (which is the sum of the Froude-Kroylov and diffraction forces, F_r is the radiation wave force, F_h is the hydrostatic stiffness force, i.e., the buoyancy force, F_{PTO} is the PTO force associated with float mass m. Here, the dominant force in this equation tends to be the excitation force F_e as it is the combination of both Froude-Krylov and diffraction forces. Each of these forces are frequency dependent meaning the calculation often requires frequency domain methods

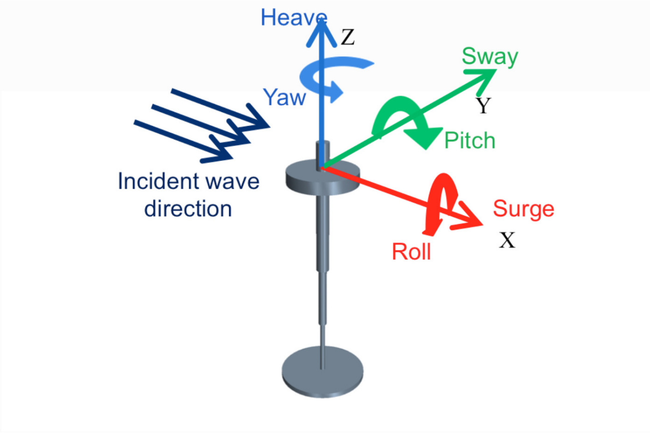

Fig. 1: Diagram showing the six degrees of freedom (6 DOF) that a free floating body experiences. There are three translational motions (heave, sway, and surge) and three rotational motions (pitch, yaw, and roll) all occurring within the incident wave. From WEC-Sim[30]

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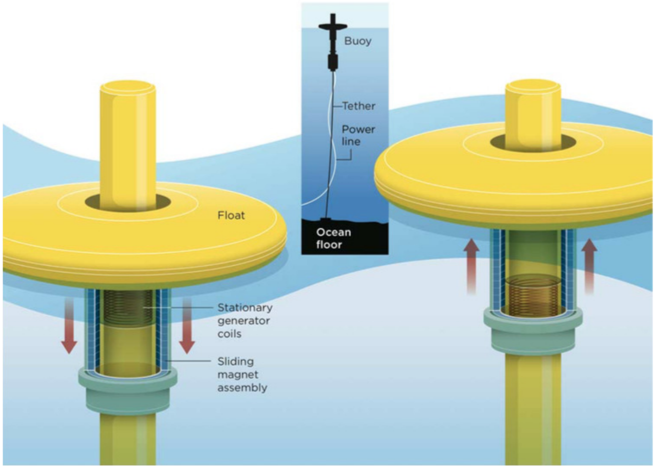

Fig. 2: L10 wave energy converter. Courtesy of Smithsonian Magazine [32].

and a Fourier transform to transform the forces into time-domain. Although the most accurate, frequency methods are often complex which make it desirable to use approximation methods instead. One way to approximate this process is to use Morison hydrodynamics to represent the excitation force as

$$F_e = A\ddot{\eta} + B\dot{\eta} + k\eta \tag{7}$$

where the terms A and B are frequency-dependent, device specific constants, and $\ddot{\eta}$, $\dot{\eta}$ are the acceleration and velocity of the wave height time-series η.

The next step in developing the wave power model is to define the power that is being extracted from the physical interactions,i.e., the PTO force. Here, we use a simplified model and define the power into the PTO mechanism as

$$P_{\text{PTO}} = -F_{\text{PTO}}v \tag{8}$$

where v is the relative velocity between the float body and the PTO mechanism. It should be noted that the negative sign in 8 is to ensure that a positive P_{PTO} corresponds to power being produced. On the basis that the wave extraction device is sufficiently moored, we can simplify the above equations such that the PTO mechanism moves with respect to a stationary reference. As a result, the relative velocity term v becomes the heave buoy velocity $\dot{z}$. Furthermore, if we assume the device is a "wave follower" (shown in Fig. (2)), then the device's velocity becomes the velocity of the water. The result of these assumptions implies the power produced becomes only a function of the wave height time-series η.

3.3 Wave Height Time-Series Calculation

The methodology with which we construct the wave time-series for the case studies that follow are predicated upon wave farm grid integration studies [20]. Specifically, it uses data from a global database of ocean buoys, the NDBC, and recreates the incident wave spectrum using a Texel-Marsen-Arsole (TMA) [33] spectrum assuming significant wave height, dominant wave period, and peak wave direction are given.

The following expressions, adapted from [34], illustrate how to generate the wave height time-series. Equations (9)-(11), show how the wave height time-series can be generated.

$$A_j = 2\sqrt{S_j(f_j, \theta_j)\Delta f_j \Delta\theta_j} \tag{9}$$

the equivalent amplitude A_j, is specified by the area under the spectrum, where $S_j(f_j, \theta_j)$ is the spectral density, and Δf_j and $\Delta\theta_j$ are the width of the bin in frequency and direction, respectively. This method also assumes a right-handed coordinate system (x, y) where x points towards the shore and y points upwards, along the shore. We define the wave height time-series η, a function of x, y, and time t, as

$$\eta(x, y, t) = \sum_{j=1}^{M} A_j \cos\left(k_j x \cos\theta_j + k_j y \sin\theta_j - 2\pi f_j t + \epsilon_j\right) \tag{10}$$

where ϵ_j is a random phase associated with each component, and the local wave number k_j is calculated for the local water depth h using linear wave mechanics dispersion relation

$$(2\pi f_j)^2 = g k_j \tanh k_j h. \tag{11}$$

Equation (10) is solved in the frequency domain by making use of a Fast Fourier Transform.

The downside to this method, unfortunately, is its inability to account for interactions between WECs. This method can only be applied to wave farms where devices are placed far enough from each other to ignore device-to-device interactions. Parks with WECs that are closely spaced devices have to consider the radiated waves created from each WEC device. It is possible, and likely, that radiated wave created from each device impact–both positively and negatively–the overall power production. With regards to the former, the radiated waves could be in phase with the dominate wave period and therefore adding to the total force exerted on the WEC device. There have been advances in optimal device placement which seek to take advantage of this fact to generate more power [35].

4 Well-Being Analysis Applied to Ocean Wave Energy

The Well-Being Analysis is an extension of the traditional MC methods discussed in Section 2. The Well-Being Analysis [11–15] gives key insights into power system reliability by leveraging deterministic and probabilistic methods. Here, the deterministic criteria provides an additional security criteria that allows each system state S_i to be categorized as either *healthy*, *marginal*, or *at-risk*. It is common to categorize the system state using either a list of pre-specified outages [36] or by looking at the system reserve margins. In this paper, we use the latter.

Under these conditions, a system state is defined as *healthy* if it has enough generation and transmission capacity to meet the current electrical demand before and after performing the deterministic criteria. In the case the system state fails the deterministic criteria, the system is classified as *marginal*. If the

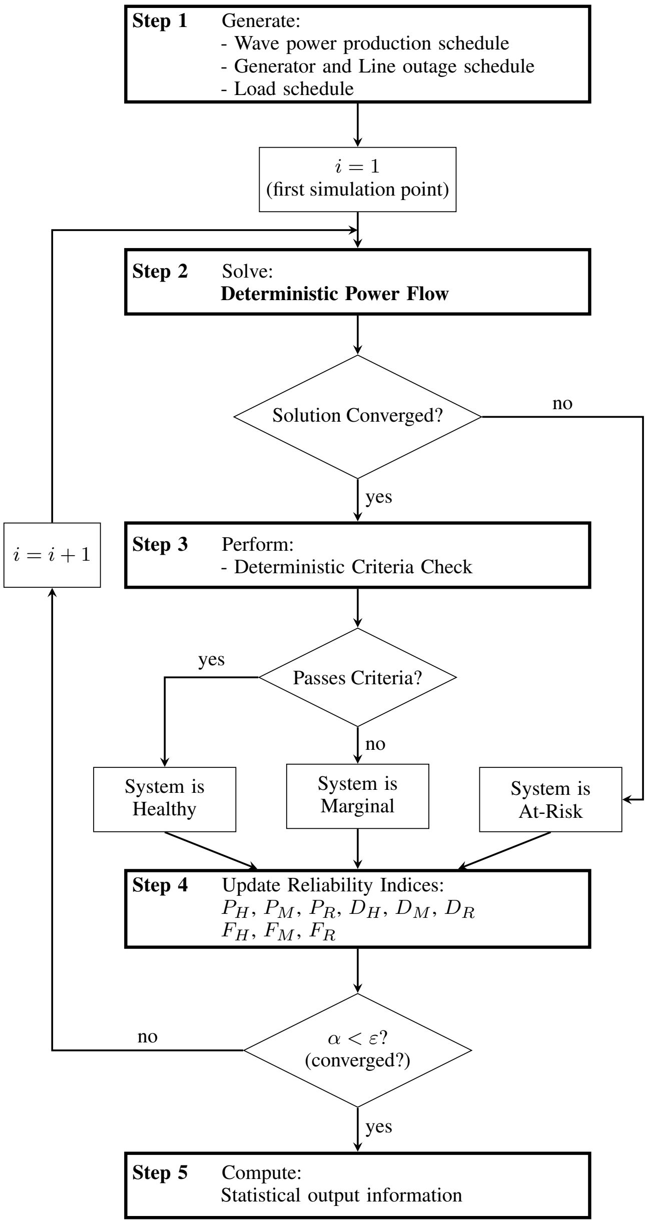

Fig. 3: Flowchart for Well-Being Analysis methodology including ocean wave energy.

power system has insufficient generation and transmission capacity before or after the deterministic criteria is performed the the system is categorized as *at-risk*. Upon classification of each system state, statistical output information can be computed to quantify the overall reliability. Here, we examine the probability (P_H, P_M, P_R), frequency (F_H, F_M, F_R), and duration (D_H, F_M, F_R) indices for each of the three states. Details for how each of these indices are calculated is found in [13, 36].

Figure 3 summarizes the proposed methodology to estimate the reliability impact that ocean wave energy has to the power system. Several years of NDBC buoy data is used–enough to capture trends that take several years to occur, such as the warm and cold patterns of El Niño and La Niña–to create the wave height time series with equations (9)-(11). Again, with the assumption that the device is a sufficiently moored wave follower, the power production is calculated using (8). The production power output is then discretized into monthly bins and probability distributions are created. This last part is necessary because limiting the simulation time to the time-series created from the NDBC data makes it is unlikely for our reliability metrics to converge. Therefore, it is necessary to sequentially sample from representative distributions to capture the seasonal and inter-annual trends in ocean conditions.

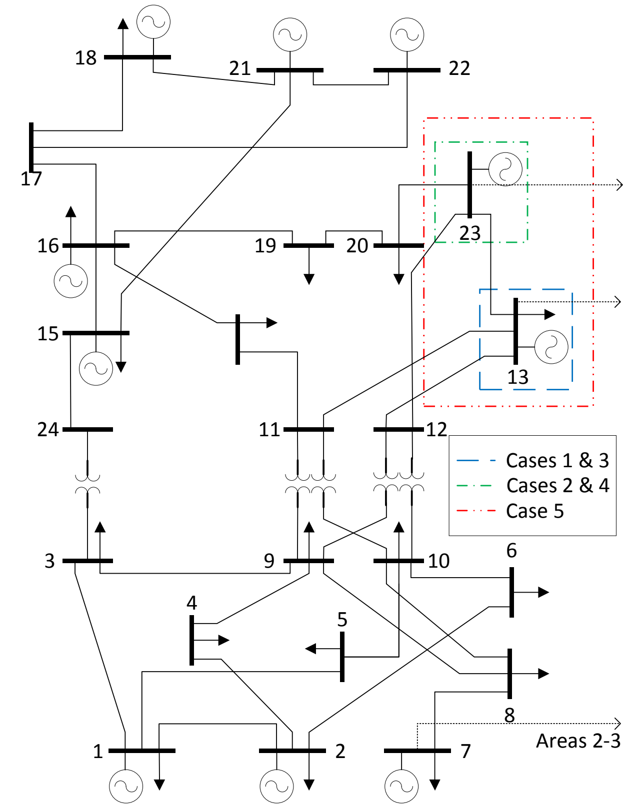

Fig. 4: One line diagram for a single area of the IEEE Reliability Test System 1996 (IEEE-RTS) illustrating wave farm generator replacements and experimental setup.

5 Results

The following sections will seek to answer the question of whether ocean wave energy has an impact to power system reliability. The experiments are setup in such as way as to identify potential seasonal, inter-annual, and geospatial trends associated with utility scale wave energy integration.

5.1 Experiment Description and Setup

For the purposes of these experiments, we make a few additional assumptions to how the WEC devices are modelled. In addition to being modelled as a wave follower, we assume that the PTO is controlled in such a way that the PTO force is proportional to velocity $F_{\text{PTO}} = B_{\text{PTO}}\dot{z}$ where B_{PTO} is the PTO dampening factor. As a result, (8) becomes $P_{\text{PTO}} = B_{\text{PTO}}\dot{z}^2$. Additionally, we assume that the devices are rated to a maximum active power output of 250 kW and B_{PTO} is chosen such that each WEC has a capacity factor of 50% for the month of January. The devices conform to the "wide-spacing assumption" are assumed to be spaced 100 meters apart (so as to ignore body-to-body interactions) and are in deep water (so as to apply linear wave theory) [31]. We should note that while the wide-spacing assumption does not prescribe a separation distance it does suggest that the bodies are separated by a distance sufficiently larger than the wavelength of the incident wave.

Fig. 5 shows the monthly power distributions, which will be used to generate the wave power schedule, for three different sites along the western coast of the United States. Namely, these sites are:

- **Station 46041**, Cape Elizabeth, 45 NM Northwest of Aberdeen, WA;

- **Station 46050**, Newport, OR;
- **Station 46047**, Tanner Banks, 121 NM West of San Diego, CA

Throughout the rest of this paper, we will refer to these sites as Station A, B, and C, respectively.

For benchmarking purposes, we use the IEEE Reliability Test System 1996 (IEEE-RTS) [37]. The system consists of 73 buses, 120 transmission lines, and 99 generators that add up to a total capacity of 10,215 MW. In addition to the usual power system data, the model contains an hourly load schedule for all 8,760 hours in a year, MTTF, MTTR, and FORs for each generation and transmission asset. The deterministic criteria used for the Well-Being Analysis is the loss-of-largest-generator whereby, in each system state S_i, the largest generator is taken out-of-service and a power flow is performed on the new system state. Lastly, the stopping condition for the MC simulations is such that the coefficient of variation of the LOLE index is less than 5%.

We implemented the proposed method in MATLAB, making use of the open-source power system optimization toolbox MATPOWER [38]. The two ways to model a renewable resource in MATPOWER are generator modeling and negative load modeling. In the former, a generator is placed on its associated bus and the power output is the value of the renewable energy power production. To ensure the generator is non-dispatchable, the rated power of the device equals its current power production. In negative load modeling, a renewable resource is modelled as a load with demand equal to the negative power produced by the resource. While negative load modeling is simpler, it is more beneficial to model the resource as a generator. For example, it is possible to model voltage limitations and voltage or power factor controls that the farm may have. Considering this, our wave farms will be modelled as a generator with a 0.95 to 1.05 p.u. voltage range and zero reactive power capabilities. Future work in this area could take into consideration reactive power control of these farms as it is typical for interconnection agreements to require both 0.95 leading and lagging power factor on the basis of FERC Order 827 [39]. Lastly, for simplicity purposes we have ensured that wave farms are always producing power; that is, never go offline for repairs. In a more realistic scenario, the farm would have several derated states based on the number of devices in the farm.

With the conditions outlined above, we perform various experiments that explore the extent of the impact that a wave energy farm has on the power system. We label these cases Case 1 through Case 5. In Case 1, we replace a single 197 MW generation unit at Buses 113, 213, and 313 (Bus 13 in the single area Fig. (4) with 197 MW wave farms characterized by Station A, Station B, and Station C, respectively. Then, in Case 2 we replace a single 155 MW generation unit at Buses 123, 223, and 323 (Bus 23 in the single area Fig. (4) with 155 MW wave farms that are characterized using the same configuration as Case 1. In Cases 3 and 4, the wave farms are placed at the same location as the previous two cases but all three wave farms were characterized by the environmental conditions from Station A. Lastly, Case 5 examines the impact when wave farms were placed electrically close together. To do this, we placed 197 MW and 155 MW wave farms (characterized the same as Cases 1), at Buses $x13$ and $x23$, respectively, in each of the three defined areas of the IEEE-RTS.

Table 1 Well-Being Indices for Different Wave Integrated Cases with Generator Replacement

Index	Base	Case 1	Case 2	Case 3	Case 4	Case 5
P_H	0.9992	0.9992	0.9988	0.9992	0.9988	0.9990
P_M	0.0001	0.0001	0.0005	0.0001	0.0005	0.0003
P_R	0.0007	0.0007	0.0007	0.0007	0.0007	0.0007
F_H	1.69	1.68	2.21	1.68	2.22	1.93
F_M	1.54	1.65	2.02	1.64	2.04	1.89
F_R	1.32	1.32	1.32	1.32	1.32	1.32
D_H	5175	5220	3954	5222	3942	4516
D_M	5.14	5.63	6.39	5.64	6.33	6.82
D_R	10.8	10.8	10.8	10.8	10.8	10.8

Base Case: Original system without wave farms
Case 1: 3x197 MW units replaced by 197 MW wave - different profiles
Case 2: 3x155 MW units replaced by 155 MW wave - different profiles
Case 3: 3x197 MW units replaced by 197 MW wave - same profiles
Case 4: 3x155 MW units replaced by 155 MW wave - same profiles
Case 5: Replace 3x155 MW and 3x197 MW units, separated by one transmission line, with wave of same capacity and profiles

5.2 *Simulation Results*

Table 1 shows the results of applying this method to the base IEEE-RTS and each of the cases listed above. Comparing Case 1 to the Base Case, we notice the replacement of traditional generating units in this scenario has a relatively small negative impact to the reliability of the power system. This impact is suggested by the decreases in P_H and D_H, as well as increases of P_M and D_M. This indicates that the system leaves the healthy state more frequently, thereby reducing the average time that the system is healthy over the simulation period. By comparing values between Case 2 and the base case, we observe a 5x increase in probability for the system to be considered marginal and a 24% decrease in the average duration that the system is healthy. We should mention, however, that although there is a large increase in the likelihood of being marginal between Cases 1 and 2, the overall probability remains low. These results suggest that even with a lower relative wave farm capacity on the grid there is a larger impact to the reliability of the system. This can be explained by the fact that geographical placement of WECs play a bigger role to the reliability of the system than the total capacity.

Cases 3 and 4 show reliability values for scenarios where the sites are all characterized by the same environmental profile. These results indicate that having wave farms characterized by the same geographical profile has no additional negative impact than having geographically different profiles. Although not shown here, any configuration of the three sites produces similar results to Cases 1 and 2. In contrast, differences between Cases 1 and 2 indicate that there is large dependence on geographical placement of wave energy farms. This effect is substantial, in that even while there are 100 MW less of wave energy capacity, the probability that the system is marginal is five times larger. This impact is also reflected in every other Well-Being index. It is important to note from Table 1 that the probability, frequency, and duration data for the at risk states are the same. These results suggest that wave energy alone does not create additional failures on the system based on the LOLG criteria. In fact, the only impact that wave energy has on the reliability of this particular benchmarking power system is how often and how long the system is close to failure.

In several real power systems, large amounts of renewable energy are connected through one or two buses in a power system. The results for Case 5 suggest that there is significant impact associated with wave farms that are connected via electrically close buses. However, looking at Cases 3 and 4, this effect is not a direct consequence of the shared environmental profile. If we pull from experiences in the wind industry, we know that there are several issues associated with multiple large wind facilities connecting to long radial lines. For example, reactive support becomes challenging as renewable resources are limited in their reactive capabilities. It is reasonable then to suggest that in future work an interesting open question will be to explore these types of problems when integrating utility scale wave energy farms.

5.3 *Capacity Support for Integrating Ocean Wave Energy*

In order to measure the amount of generation support that is beneficial for the proposed wave energy configurations, we simulate actions to restore the system to healthy status anytime that it is deemed marginal. Specifically, we homogeneously increase the capacity of each other wave generator in the system buy a small incremental amount. We repeat this process until the system is healthy or the amount of additional generation capacity is greater than 50% of the nameplate system capacity. The probability distribution function and cumulative distribution function for this experiment are shown in Fig. 6. This experiment shows that by adding 300 MW of generation capacity–or 3% of the total system

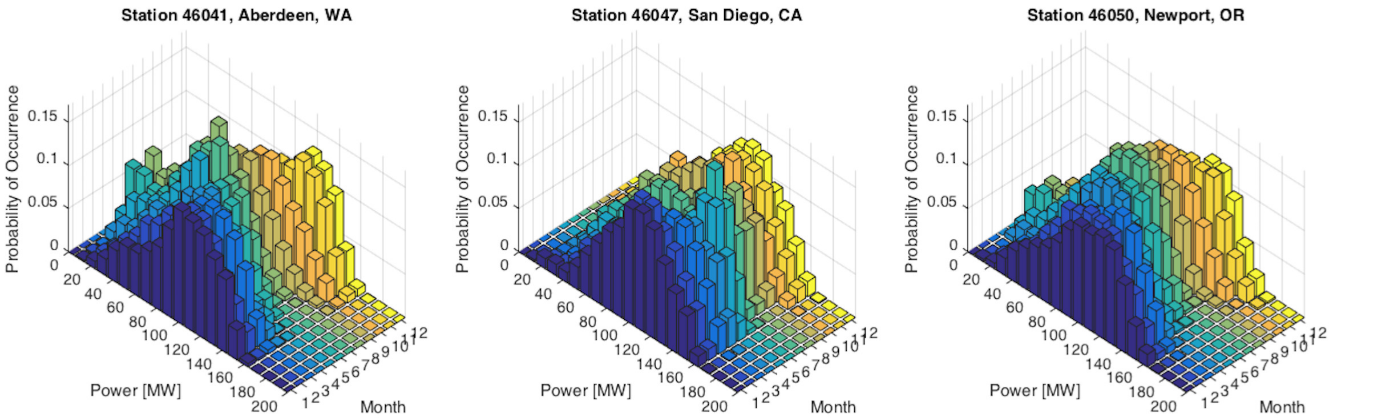

Fig. 5: Monthly probability distributions for three different wave farms located on the western coast of the United States. Fifteen years of NDBC data is gathered to capture monthly variability of power production

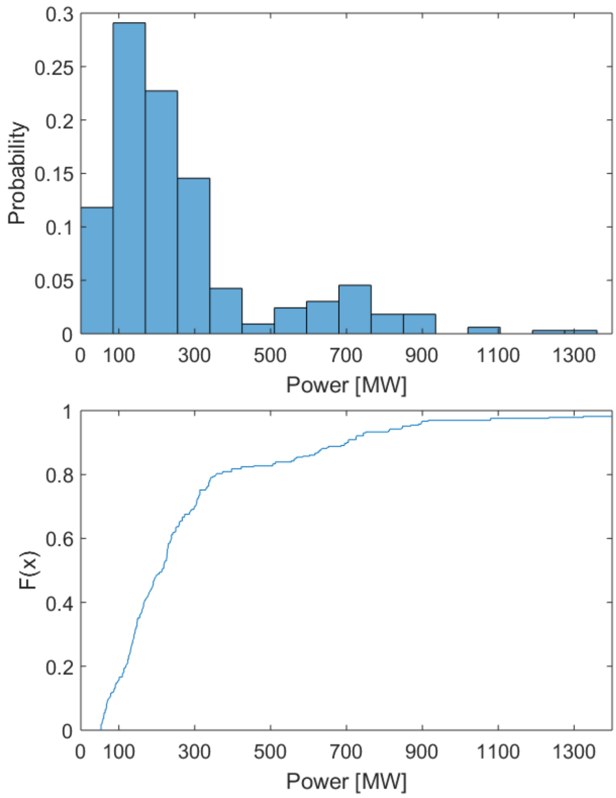

Fig. 6: Probability distribution function (top) and cumulative distribution function (bottom) showing how much additional power the system in Case 1 needs for it to be changed from marginal to a healthy state. The data shown is binned to the nearest 100 for clarity.

capacity–the number of marginal cases is reduced by approximately 60%. This implies that because the wave energy is a variable resource that there is still a strong need for dispatchable generation.

For completeness, we show the Well-Being indices for this case, labeled as Case 6, and the comparative Case 1 in Table 2. While the reduction in P_M is expected, we see that there are significant changes to all of the frequency and duration indices. We attribute these changes to our efforts to reduce each marginal state. For example, imagine that a combination of generation, transmission, and wave schedule creates a period of time–say two weeks–where the system would be marginal. Next, as we add more capacity to the power system some, but not all, system states are now healthy. However, if some of these marginal states are unable to be saved we

Table 2 Well-Being Indices for Case 1 and Homogeneous Unit Capacity Increase

Index	Base	Case 1	Case 6
P_H	0.9992	0.9992	0.9993
P_M	0.0001	0.0001	0.0000
P_R	0.0007	0.0007	0.0007
F_H	1.69	1.68	1.70
F_M	1.54	1.65	2.53
F_R	1.32	1.32	1.31
D_H	5175	5220	5138
D_M	5.14	5.63	2.31
D_R	10.8	10.8	10.8

Base Case: Original system without wave farms
Case 1: 3x197 MW units replaced by 197 MW wave - different profiles
Case 6: With Case 1 setup, homogeneously increase system capacity if system is marginal

have then changed the frequency, and thereby duration, the system transitions from one state to another. The gross effect is that we have reduced the overall probability and duration is marginal but at the cost of increased state transitions.

5.4 *Effect of 100% Reliable Wave Units*

In the experiments listed above, of the many assumptions we make the most important one–at least with respect to reliability–is that we assume each unit is 100% reliable. As mentioned very briefly before this assumption is unrealistic. In this section the authors would like to discuss some of the possible implications of this assumption and what a more realistic scenario would look like.

Let us assume that the each wave generator follows a similar generator availability as the same size generators they replaced–95%. Due do the non-dispatchable nature of the resource we would be correct in suspecting that the reliability indices, or at least the probability of marginality, will be worse. However, we should be aware of the fact that its the MTTR and MTTF, which are important quantities for sequential MCS, are quite large in this scenario. This is likely due to these sources being in a highly controlled environment where the probability of there being unexpected failures are quite low. In ocean wave energy, the devices will be exposed to the harsh conditions of the ocean. Salinity will corrode parts faster and those parts will take longer to repair due to them being harder to get to. With this considered it is likely that the MTTF will be lower and the MTTR longer indicating that 95% availability may be unrealistic. Reports from the offshore wind industry suggests that a baseline for offshore technology could be 93-94% [40]. However, this is a much more developed industry with well established operation and maintenance strategies.

6 Conclusion

The work presented in this paper illustrates steps toward comprehensive power system reliability studies that incorporate utility-scale wave energy farms. Leveraging a combined deterministic and probabilistic approach enhanced by wave energy modeling, we have examined the impact that wave energy has on a benchmarking power system at hourly intervals. The results suggest that, in this particular system, wave energy has a small but negative impact observed at hourly timescales. Importantly, the small observed negative impacts do not create additional failure states, only an increase in the probability that the system is marginal. Lastly, on the hourly model we were able to mitigate marginal system states with a relatively small increase in system capacity. In fact, by adding approximately 300 MW of controllable generation we can reduce 60% of all marginal cases.

A major goal of this work is to provide a model with tunable fidelity that can be incorporated meaningfully to many different types of studies. In doing so it was necessary to develop a benchmarking study that can be used as a reference for subsequent research. Future work will address some of the modeling limitations in the current approach–particularly how to model the power system and WEC devices. We will include modeling of dependent outages in order to investigate whether or not wave energy farms impact the mechanisms of cascading failure. We will also model multiple wave farm configurations (and substation connections) that include distinct WEC models capturing state-of-the art commercial designs.

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