Uncertainty Cost Functions for Wave Energy

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Abstract: - Wave energy is considered as an important energy source for people living near coastal areas to meet their basic energy needs. Innovative and new technologies can be used for this energy utilization to run the loads from sea waves. Due to its uncertain power availability, we can use uncertainty cost functions based on probability distributions for the availability of the operation of the wave energy microgrid. These probability distributions are based on several mapping models designed for the wave energy, wave height, and wave speed mapping to make the energy more stable and reliable. In contrast to other renewable energy sources, wave energy is inherently unpredictable, making it impossible to model with a single, globally applicable probability distribution function (PDF). The prediction of the behavior of primary wave energy for this purpose is completely based on several probability distribution functions (PDFs) which can be considered as the best for all conditions. In this paper, we have used the Weibull-Rayleigh probability distribution model to develop the uncertainty cost function for wave energy. The Monte-Carlo process is carried out to get the results supported by the Rayleigh probability distribution model consisting of wave height, and uncertain cost histograms. Cost is minimized by using the Weibull Rayleigh model for both overestimation and underestimation costs of wave energy. Monte-Carlo simulation results are further compared with analytical calculation and error between them.

Key-Words: - Microgrids, Renewable Energy Resources, Stochastic Processes, Wave Energy, Probability Distribution, Variable Change Theorem, Weibull-Rayleigh distribution.

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1 Introduction and State of Art

The energy which is obtained from sea waves' movements and their motion is called wave energy and this energy has many benefits in the context of energy. The prediction of behavior of primary wave energy for this purpose is completely based on several probability distribution functions (PDFs) which can be considered as the best of all cases. The appropriate PDF from several choices based on important factors with specific characteristics of the given site, we can collect the wave energy with all variable parameters, available wave energy historical data, and analysis based on a modeling approach to get the required outcomes, [1].

Using the kinetic and potential energy of ocean waves, wave energy offers an enticing way to guarantee a renewable energy source that is both ecologically benign and sustainable for use worldwide. Wave Energy Converters (WECs) are carefully designed devices placed strategically in oceans to convert wave motion into electrical energy, [2], [3].

These WECs can be divided into different kinds according to how they function, [4], [5], [6]:

- Point absorbers: These independent constructions use internal machinery to transform the mechanical energy they absorb into electricity as they oscillate in response to wave motion.

- Overtopping devices: Featuring an inclined ramp, the structure is overtopped by oncoming waves, which fill a reservoir and power turbines or other electricity-generating devices.
- Oscillating water columns (OWCs): Air inside partially submerged chambers is compressed as a result of the chamber's ability to absorb wave rise and fall. After that, the compressed air powers turbines to produce electricity.

But in order to precisely forecast wave behavior and maximize WEC design and operation, complex modeling approaches are required because of the inherent diversity of wave parameters. Modeling wave energy is essential for [7], [8]:

- Resource assessment: Calculating the potential wave energy that is available at a certain site.
- WEC design optimization: Creating a model of the interaction between waves and structures to help create reliable and effective WECs.
- Forecasting power production: Estimating how much electricity a WEC farm is likely to produce.

Through the integration of many elements such as bathymetry, wave climate, and WEC features, these models facilitate the assessment of the practicability and efficacy of wave energy initiatives by scholars and practitioners. Nonetheless, effective wave behavior prediction is essential for WEC design and operation. In contrast to other renewable energy sources, wave energy is inherently unpredictable, making it impossible to model with a single, globally applicable probability distribution function (PDF).

This situation results from the interaction of multiple factors [9], [10], [11]:

- Site-Specific Oceanography: Wave patterns at a particular place are greatly influenced by the water depth, bathymetry (seabed composition), and the dominant wave climate.
- Data Availability and Quality: The extent and quality of past wave or wind speed measurements play a major role in choosing the right PDF.
- Goals for Modelling: The best PDF depends on the model's goal, which could include wave height prediction, energy capture potential evaluation, or analysis of severe wave events (such as rogue waves).

As such, choosing the best PDF requires a careful assessment of these factors.

1.1 Common Probability Distributions in Wave Energy Modelling

The most important several probability distributions which can be used in order wave energy modelling are as follows [12]:

Rayleigh Distribution: Wave amplitude is well-modeled by this two-parameter function. The Rice-Rayleigh distribution, which characterizes a narrowband signal's envelope, serves as its basis. When the underlying signal is completely sinusoidal, the Rayleigh distribution becomes a special instance and is especially useful when wind speed data is provided. This is due to the fact that wind speed and wave height are known to be correlated.

Weibull Distribution: The three-parameter Weibull distribution, which is comparable to the Rayleigh distribution, is used to represent wave height or wave energy as a function of wind speed. This probability distribution has more degrees of freedom as compared to the Rayleigh probability distribution. In addition, it can apprehend wave height fluctuations and a large range of wind speeds. This probability distribution has characteristics about its tail behavior and enables several cases of modeling the systems having skewness of different levels.

Generalized Pareto Distribution, or Pareto Distribution: Pareto Distribution has the characteristics of heavy-tailed along with a power law tail. This characteristic of pareto probability distribution supports to model severe wave events for such enormous waves. This probability distribution is more useful in calculating the energy potential of waves. It has the capability to measure and depict the probability of low-frequency and high-impacted events of waves.

Lognormal Distribution: The lognormal probability distribution function is used to model the wave energy distribution and is more productive when the data represents lognormal distribution and has positively skewed a long tail. The natural positive skewness due to the existence of massive wave events can be frequently observed in wave energy data. In this distribution, it is easier to capture massive wave events than smaller ones.

Specialized Sea Wave Distribution: This distribution function has the capability of capturing the combined distribution of wave height and wave period due to its additional characteristics of capturing particular probability distributions. In addition, it has the properties to demonstrate a more accurate image of the wave climate of a specific place. So, they are producing frequent results in order to show in-depth field observations or numerical models.

It is a more critical procedure for data availability and its quality which has a big impact on probability distribution function (PDF) selection. There are several statistical methodologies to select the best distribution for a given dataset. For example, moment matching, or maximum likelihood estimation. In order to validate the selected model, a thorough comparison with measured wave data is used to guarantee the model's correctness in predicting wave energy behavior.

Considering more about the uncertainty cost functions for wave energy, we have used different PDFs in wave energy modeling in this research work. Site specifications and site characteristics can play an important role in deciding the right PDF in the context of data availability and quality. We have other statistical approaches for fitting the data in order to determine a useful probability distribution for data set availability. In the end, we need to validate the model in order to find out its accuracy, forecast ability, and wave energy speed behavior, [3].

Based on the previous literature in this section I and assumptions made in section II, we have developed the analytical uncertainty cost functions to deal with uncertainty behavior from wave energy generation (section III).

2 Problem Formulation: Wave Available Power from Wave Energy

The Weibull and Rayleigh models for probability distribution are more useful in order to do modeling for the wave energy, wave height, and wave speed. We can formulate a problem based on the data available in the context of wave energy.

2.1 Probability of Sea Wave Height

Applying different probability distribution functions (PDFs) is necessary to characterize the stochastic nature of sea wave heights. The modified Rayleigh distribution (sometimes called the Rice distribution) is one such method. The amplitude of ocean waves as a function of particular factors is effectively modeled by this distribution.

The modified Rayleigh distribution's mathematical basis is its capacity to depict a narrowband signal's envelope. Essentially, it expresses the amount that arises from the addition of two separate parts, [13], [14] :

- Random component: Caused by wind seas, swells, and local wind influences, among other things, wave heights exhibit inherent variability.
- Deterministic component: This component shows foreseeable changes in wave heights, which are frequently related to tidal effects or the existence of an underlying current that is always present.

Consequently, the modified Rayleigh distribution is useful in modeling the combined influence of these two contributing components in the context of wave energy. It recognizes the existence of a deterministic component that might be impacted by tides or prevailing currents, on top of a random component that is probably caused by wind and other ephemeral causes.

However it is important to recognize that the underlying assumptions determine whether the modified Rayleigh distribution can be applied. Among these presumptions are:

- Narrowband process: It is assumed that the underlying wave field is narrowband, which denotes a dominating wave frequency and a minimal spectral width.
- Gaussian noise: It is assumed that the random element has a Gaussian distribution, [15].

The sea waves have different heights, speed, and energy. They can be mapped based on the probability distributions in order to model the wave height, speed, and energy. We can modify one of these probability distributions in order to represent wave height, wave speed, and wave energy. For this purpose, we can use the Rayleigh probability distribution or the Rice probability distribution. We can use these probability distributions in order to model the wave energy amplitude which is the function of some specific parameters related to probability distribution, [16].

In this paper, we have used modified Rayleigh distribution as a continuous probability distribution function which describes the magnitude of signal height. The signal height is basically the sum of the two independent components of signals. One of these components is a random signal having Rayleigh probability distribution and the other component is called a constant deterministic signal component. Wave energy and wave height are the combination of random components based on the variability in natural waves and deterministic component is based on tide or wind intensity, [5].

The probability density function (PDF) of the modified Rayleigh Distribution is given by:

$$f\ (h) = \frac{h}{\sigma^2} \exp\left(-\frac{h^2+{h_0}^2}{2\sigma^2}\right) I_0 \left(\frac{h h_0}{\sigma^2}\right) \quad (1)$$

where:

- $f\ (h)$ is the PDF of the wave height h
- σ is the scale parameter that determines the dispersion of the distribution
- h_0 is the displacement parameter that represents the deterministic component
- I_0 Is the modified Bessel function of the first type and order zero

In this probability distribution, we can use the model that is mapped for the height of waves in the ocean with some specific time period, and wave location. The important factor that is to be considered is ocean wave height distribution is completely dependent on wave location and meteorological conditions of this wave. In order to formulate this into a model, we need observational data or information. In this context, the formulated model basically represents an accurate model of wave energy with its specific and particular location, [6].

Modeling sea wave elevation over a certain temporal frame and geographic area is one use for the modified Rayleigh distribution. It is crucial to recognize that wave height distributions have inherent spatiotemporal variability. This fluctuation results from the interaction of multiple factors:

- Geographical location: The features of wave fields at a particular site are greatly influenced by bathymetry (seabed topography), proximity to coastlines, and local weather patterns.
- Meteorological conditions: Wave production and propagation are dynamically modulated by wind speed, wind direction, and prevailing weather systems, resulting in variations in wave height distribution.

Therefore, in order to accurately reflect the wave energy supply at a given area, site-specific data or validated numerical wave models are essential.

Significant wave height (*Hs*) is used in this study as the main indicator of wave energy. A reliable indicator of the wave climate is Hs, which is the average height of the highest one-third of the waves in a given sea state. The variability of wave height at a given location and time is statistically characterized by the probability distribution function (PDF) of *Hs*, commonly known as the sea wave distribution.

It is important to acknowledge that there is not a single PDF that can be used to all situations and places that completely characterizes wave height distribution. As was previously indicated, the modified Rayleigh distribution is a useful tool, but its usefulness is dependent on certain assumptions that may not hold true in all situations.

The modified Rayleigh probability distribution for this can be expressed in the following probability density function (PDF).

$$f\ (H_S) = \frac{H_s}{\sigma^2} \exp\left(-\frac{H_S^2}{2\sigma^2}\right) \quad (2)$$

where:

- $f\ (H_S)$ is the PDF of the significant wave height H_s
- σ is the scale parameter that determines the dispersion of the distribution

We can describe this distribution as the probability of observational data about the significant wave height based on specific time interval and location. This probability distribution is considered as the function of and it represents the variations in the wave heights. It is very important to consider this modified Rayleigh probability distribution as an approximation that has all types of properties and characteristics of wave height distribution, [17].

In practical cases and applications, we need to develop and design more specific wave energy models that are based on observational data and location in order to optimize the model, [8]. We are able to find the probability distribution of wave height and wave power by using this distribution model. The direction of the wind, depth of water, seafloor variations, and topography are the additional parameters including and affecting the observational data and formulated models, [9], [10].

The modified Rayleigh probability distribution is used to establish a probabilistic framework to determine the probability of meeting a particular significant wave height (Hs) in a given time frame. A single parameter σ (sigma) is the foundation for this purpose for mathematical measurement of the variability or dispersion in wave heights. Critically, we can recognize several inherent drawbacks in this approach, [13], [16]. A rough approximation is observed in Rayleigh distribution, and it does not represent the full range of properties in sea wave height distribution in all situations. Alternative models are available for more investigations when there are deviations in basic assumptions about the model like narrowband wave processes or Gaussian noise.

Real-world applications of wave energy are making the strategy to use observational data or verified site wave models. Both data sources and models must have the ability for other variables inclusion have substantial impact on wave height distribution, giving accessible potential wave energy. Some extra factors influencing the wave energy are as follows, [17], [18]:

- Wind direction: To determine wave formation and propagation patterns, we need to find the predominant wind direction influenced by the distribution of *Hs*.
- Wate depth: The distribution of wave height at a given site is affected by water depth and seafloor topography wave properties which are modulated by using bathymetry.
- Seafloor topography: The seabed topography produces shoaling and refraction of sea waves which influences both the distribution of *Hs* and the extracted amount of wave energy.

Wave energy supply and its variability at a specific site is depicted more accurately by using observational data and site-specific models considering the above extra factors.

2.2 Relationship between Significant Wave Height and Available Injection Power

It is well well-known, [19], [20], relationship between wave height and power produced from it. The power produced from sea wave energy is injected into the power grid system as per energy needed to fulfill the loads. The wave energy is dependent on several factors like energy conversion system design, site location and characteristics, and sea atmosphere/climate. The basic relationship between significant wave height and available injection power can be formulated by describing the effects of wave height on power generation.

In the context of wave energy conversion, the relationship between significant wave height (*Hs*) and the extractable electrical power that may be added to the grid is complex and influenced by a number of parameters as follows:

- Wave Energy Converter (WEC) Design: The quantity of power that can be extracted from a particular wave climate is greatly impacted by the intrinsic design features of the WEC, such as its power capture efficiency and operational constraints.
- Site-Specific Characteristics: The wave energy supply that is accessible at a given area is mostly determined by bathymetry (seabed topography), water depth, and local wave climate.
- Sea Conditions: The potential wave energy that is accessible is dynamically influenced by prevailing weather patterns, which include wind direction, speed, and wave characteristics.

However, a simpler connection can be developed to provide a basic grasp of the link between wave height and extractable power. The power generated from wave energy is found by using the kinetic energy concept based on wave motion. The wave height factor can influence kinetic energy. The kinetic energy present in wave motion is captured by wave energy. *Hs* is a crucial sign of the wave energy potential in a given area. A generalized approximation of the relationship between Hs and the available wave power density (*P*) is given by the following formula:

$$P = C.\rho.g.H_S^2.T.A \tag{3}$$

where:

- P is the available Power
- C is the conversion coefficient that takes into account the efficiency of the capture device energy and other factors related to system design
- ρ Is the density of seawater
- g is the gravitational acceleration
- H_s is the significant wave height, which is a statistical measure of wave height
- T is the wave period, which is the time between two significant crests
- A is the effective capture area of the device

This formula for power available is in its simplified form but its exact formula or relationship is dependent on specific factors of the energy conversion system and sea waves site climate.

Moreover, the efficiency of energy availability can be affected by wave variations, mechanical effects, and conversion system efficiency, [19].

In short, we can say that the height of the wave is important in the context of finding the power availability in wave energy. We can define the relation in the form of the model by using this formula in equation (3) based on system parameters and other sea conditions, [20].

Although the formula that is provided provides a first evaluation of how wave height affects extractable power, it is critical to recognize that it has inherent limitations. There is fluctuation in the relationship between available wave power density (Pw) and Hs based on a number of factors:

- Wave Energy Converter (WEC) Specifics: The quantity of electrical power that can be extracted from a certain wave climate is greatly influenced by the design of the power take-off (PTO) system and its conversion efficiency.
- Site Conditions: The wave energy resource that may be captured depends on elements including bathymetry, ocean depth, and dominant wave characteristics.
- Wave Variability: The efficiency of energy-capture devices may be impacted by the intrinsic stochastic nature of waves, which are defined by fluctuations in height, period, and direction.

Moreover, the maximum extractable power under particular sea conditions is largely dependent on the mechanical strength and operational constraints of the WEC.

Significant wave height (*Hs*) is essentially a crucial marker of the wave energy potential at a specific site. A fundamental understanding of the connection between Hs and available wave power density is offered by the generalized formula. Real-world applications, however, demand thorough modeling techniques that take into account:

- Specifics of the WEC design, such as the PTO system's effectiveness.
- Advanced wave modeling approaches to account for extreme wave events and wave variability;
- Site-specific features such bathymetry, water depth, and local wave climate.

Researchers and engineers can create more accurate evaluations of the wave energy resource and the functionality of WEC systems under different operating scenarios by taking these extra factors into account, [21].

2.3 Uncertainty Cost of Wave Energy

In this research work, we have formulated an analytical cost function which is derived from an expression consisting of significant wave height, probability distribution, and occurrence, [12]. The formulated problem is solved by having an analytical cost function which is obtained from analytical expression derived by using the significant height of sea waves and their probability of occurrence.

There are the following two cases connected with the uncertainty cost of wave energy.

To do this, the following expression must be solved:

$$Underestimated\ Expected\ Cost = \int_{P_s}^{\infty} C_v\,(P - P_s)\, f(p).dP \tag{4}$$

$$Overestimated\ Expected\ Cost = \int_{V}^{P} C_o\,(P_s - P)\, f(p).dP \tag{5}$$

where:

- $f(p)$ is the PDF of the of P

In this way, considering the following from sections 2.1 and 2.2, we have:

$$P(H_S)$$

$$\updownarrow$$

$$f(H_S)$$

$$\updownarrow$$

$$f(P) = ?$$

3 Problem Solution: Analytical Development for Wave Uncertainty Cost Functions

The problem presented in Section 2.3 can be solved by using following mathematical analytical development.

$$P(H_s) = C.\rho.g.T.A.H_s^2$$
$$P(H_s) = K_1 H_s^2 = g(H_s)$$
$$P = K_1 (H_s^2)$$

$$H_s = \pm \tag{6}$$

We can obtain the inverse of g and its derivative as follows:

$$g^{-1}(p) = \pm\sqrt{\frac{P}{K_1}} = \pm\frac{1}{\sqrt{K_1}}\, P^{1/2}$$

$$\left\{ -\frac{cu\left(K_2^2 e^{\frac{-P_s}{K_2}} - K_2(\lim_{P\to\infty} e^{\frac{-P}{K_2}}(P - P_s + K_2\right.}{K_2} \right. \tag{7}$$

$if\ K_2 \neq 0$

$$\frac{dg^{-1}(p)}{dp} = \frac{1}{\sqrt{K_1}}\,\frac{1}{2}\,P^{-} = \quad \frac{1}{2\sqrt{K}} \tag{8}$$

The changes in variable expression can be applied as follows by using the Variable Change Theorem:

Consider that f_x as the probability density function of x, and y.

Where y = g(x)

Then the probability density function of y can be written as follows:

$$f_y(y) = f_x(g^{-1}(y)) \left|\frac{dg^{-1}}{dy}\right. \tag{9}$$

Based on variable change theorem expression, we can calculate the following costs.

3.1 Penalty Cost Due to Underestimate

The underestimated expected cost can be written as:

$$UEC = \int_{P_s}^{\infty} C_v(P - P_s)\,.\frac{1}{2K_1\nabla^2}\,.e^{\frac{-P}{2K_1\nabla^2}}\,.dP$$

$$UEC = \frac{C_v}{2K_1\nabla^2}\int_{P_s}^{\infty}(P - P_s)\,.e^{\frac{-P}{2K_1\nabla^2}}\,.dP$$

$$UEC = \frac{C_v}{K_2}\int_{P_s}^{\infty}(P - P_s)\,.e^{\frac{-P}{K_2}}\,.dP$$

Where: $K_2 = 2K_1$

$$UEC = \frac{C_v}{K_2}.K_2 \left|[P_s - P - K_2]\,e\right. \tag{10}$$

Suppose that the tidal technology is injecting the power with its maximum capacity, and this maximum capacity value is range between 10-20 times more in value than the power which is programmed or forecasted. Then the underestimated expression for uncertainty cost in both cases are as follows:

Case 1: 10 times more value

$$cu\,e^{\frac{-10P_s}{K_2}}\left(9P_s + K_2 - K_2 e^{\frac{9}{l}}\right. \tag{11}$$

Case 2: 20 times more value

$$cu\,e^{\frac{-20P_s}{K_2}}\left(19P_s + K_2 - K_2 e^{\frac{19}{K}}\right. \tag{12}$$

We can write it in its generic form as follows:

$$\left| -\frac{cu\left(P_s K_2\left(e^{\frac{-P_s n}{K_2}} - e^{\frac{-P_s}{K_2}}\right) - K_2\,e^{\frac{-P_s n}{K_2}}(K_2 + P_s n) + K_2 e^{\frac{-P}{K}}\right.}{K_2}\right. \tag{13}$$

Where parameter n value can be found based on experiments by using tidal energy technology.

3.2 Penalty Cost Due to Overestimate

The Overestimated expected cost can be written as:

$$OEC = \int_{0}^{P_s} C_0(P_s - P)\,.\frac{1}{2K_1\nabla^2}\,.e^{\frac{-P}{2K_1\nabla^2}}\,.dP$$

$$OEC = \frac{C_0}{2K_1\nabla^2}\int_{0}^{P_s}(P_s - P)\,.e^{\frac{-P}{2K_1\nabla^2}}\,.dP$$

$$OEC = \frac{C_0}{K_2}\int_{0}^{P_s}(P_s - P)\,.e^{\frac{-P}{K_2}}\,.dP$$

Where: $K_2 = 2K_1\nabla^2$

$$OEC = \frac{C_0}{K_2}.K_2 \left|[P - P_s + K_2]\,e^{\frac{-P}{K_2}}\right|$$

$$OEC = \left|\frac{co(K_2^2 e^{\frac{P_s}{k_2}} + P_s K_2 - P_2^2)}{K_2}\right| \tag{14}$$

4 Simulation and Validation

In Figure 1, the Monte-Carlo process is utilized in order to get original simulation results supported by Rayleigh probability distribution model based on significant wave height, and uncertainty cost histograms. Histograms are showing the relationships between significant wave height, cost due to underestimation and overestimation and power. Cost is minimized by using the Weibull-

Rayleigh model and then this model results are compared with analytical results.

The simulation results show the costs associated with estimated power in power electric vehicles (PEVs) relevant to wave heights and dispatched power [13]. We have compared the results obtained from the Monte-Carlo simulation with the results obtained from analytical development and calculations.

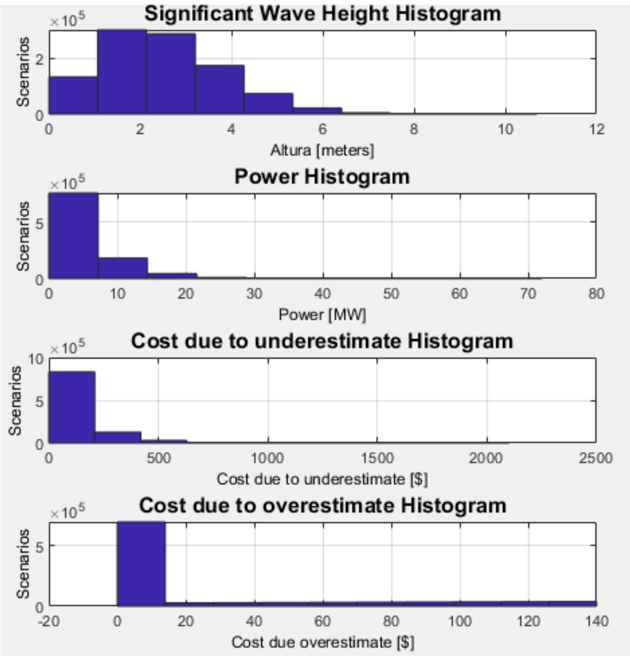

Fig. 1: Weibull wind speed and Uncertainty cost

These simulation results show the expected cost insights and the accuracy of these results by comparing them with the analytical approach as shown in Figure 1.

We have developed a total uncertainty cost functions histogram based on both cases; the overestimation and underestimation parts as shown in Figure 2.

Financial cost of wind energy is much more than the energy produced from any other resource due to its highly uncertain behavior. We cannot compare wind energy cost to other energy resources cost due to low wind energy value. The Monte-Carlo process is utilized in order to get original simulation results supported by the Rayleigh probability distribution model for significant wave height, and uncertainty cost histograms as shown in Figure 1. Histograms show the relationships between significant wave height, cost due to underestimation and overestimation, and wave power. Significant wave height, wave power, cost due to underestimation, and cost due to overestimation are presented in Figure 1. In overestimation of cost, the cost of wind energy is estimated too high while its actual value is low. On the other hand for underestimation of cost, the cost of wind energy is estimated too low and its actual value is high. Cost is minimized by using the Weibull-Rayleigh model and the results are shown in Figure 1.

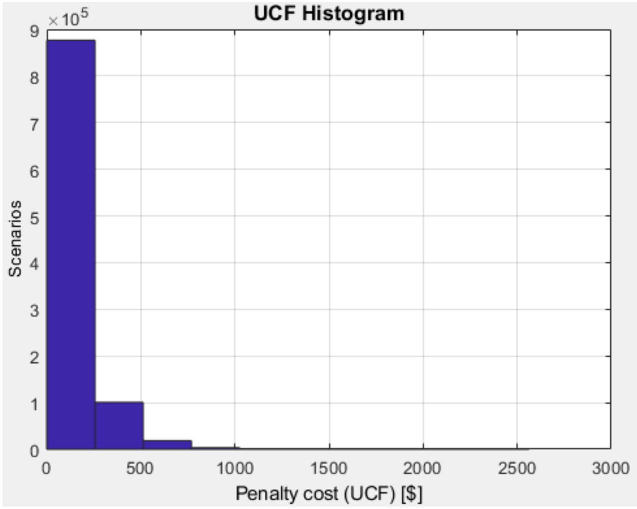

Fig. 2: UCF histogram

The complete simulation process has several steps in order to get the complete results of both underestimated and overestimated uncertain costs. These steps are basic steps for developing a Monte-Carlo simulation in order to analyze power estimation error cost for wave energy scenarios.

These steps are as follows:

a. **Initialization of Constants:**
The developed code in Matlab has an initialization process of several constants like dispatched power (P_S), a factor of scaling, No. of trials (N), costs for underestimation (CU), costs for overestimation (CO), and K_1 coefficient values.

b. **Random Generation:**
After initialization, the iteration loop generates the significant wave height (Hs) random values by using Rayleigh probability distribution based on an Escala (a scale parameter). The power (Pe) calculations are done by using the parameters K_1 and Hs. The dispatched power Ps and generated power Pe are then compared to get the costs for both underestimation (CU) and overestimation (CO).

c. **Histogram Plots:**
The developed code basically generates the histogram plots by using significant wave height, power, and both cost underestimation and overestimation.

d. **Total Cost Calculation:**

To get the total cost, we have added both the costs, the cost for underestimation and the cost for overestimation.

e. Analytical Calculation:
The analytically developed calculations are used to estimate expected costs for both underestimation and overestimation based on the calculations of dispatched power Ps, all coefficients, and a constant n. These results and calculations are performed using an outside iteration loop.

f. Output:
The output values are obtained by using the command print in the Matlab code. This code actually prints the mean values of costs for both underestimation (xu1) and overestimation (xo1) as follows:

1. Expected total cost based on Monte-Carlo Simulation.
2. Expected total cost from Analytical Calculation.

By using these two scenarios, we also calculated the error between both the Monte-Carlo simulation and Analytical calculations, [14].

In general, this Monte Carlo simulation looks into the financial effects of inaccurate power estimation in the context of wave energy. It provides information about predicted expenses and the accuracy of the analytical method in comparison to the simulation by comparing the results gained through simulation with those produced from an analytical approach, [9], [10], [11].

This code simulation results show the costs associated with estimated power in power electric vehicles (PEVs) relevant to wave heights and dispatched power. We have compared the results obtained from the Monte-Carlo simulation with the results obtained from analytical development and calculations. These simulation results show the expected cost insights and the accuracy of these results by comparing them with analytical methodology.

5 Conclusion

Wave energy is considered as a renewable energy source which can be integrated with the grid. It can provide the energy requirements for the population near the coastal area. Innovative and new technologies to capture wave energy are used for its utilization for the loads to be run. Due to its uncertain availability, we have used uncertainty cost functions based on probability distributions. These probability distributions are based on several mapping models designed for wave energy, wave height, and wave speed mapping. We have used the Weibull-Rayleigh probability distribution model in order to minimize the uncertainty cost of wave energy and minimize the cost function based on observational data or information. The formulated model has represented an accurate model for wave energy with its specific and particular location and wave height. Simulation and analytical based results generated an error which will be the future approach to minimize it.

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