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Article

Real option valuation of an emerging renewable technology design in wave energy conversion

Abstract: The untapped potential of wave energy offers another alternative to diversifying renewable energy sources. However, development costs to mature the technology remain as significant hurdles to adoption at scale. Here, we conduct a real option valuation that includes the uncertain market price of electricity and demonstrate the probability that the project's embedded option value can turn a negative net present value wave energy project to a positive expected value. This change in investment decision uses decision tree analysis and models the uncertainty as a risk-neutral stochastic process. We also show how our results are analogous to a financial out-of-the-money call option. Our results highlight the distribution of outcomes and the benefit of a staged long-term investment in wave energy systems to better understand and manage project risk.

Keywords: wave energy; real options; valuation; decision tree; stochastic process

1. Introduction

Wave energy conversion (WEC) technology has yet to be introduced at scale, in part due to levelized cost of energy (LCoE) estimates remain higher than other energy alternatives and design standards have yet to appear. However, Loth et al (2022) suggest that the use of LCoE is questionable for renewables, like wind and solar, since this metric excludes the time-varying price of electricity. Further, Aldersey-Williams and Rubert (2019) illustrate that LCoE also may not include the volatile price of fuel and often provides a single value, rather than a distribution of outcomes. Lastly, to gain private financing, others have suggested that more traditional valuation measures should be used, like Net Present Value (NPV).

"If very large wave energy installations are to be privately financed then this will involve pension funds and other very large investment funds and these investors will compare wave energy to other investment opportunities outside the power generation sector. In this case NPV or IRR should be preferred over LCoE."

– Pecher and Kofoed (2016), p. 116.

So, this paper will focus on developing an estimate of NPV to better inform non-governmental investors. In the sections that follow, we will conduct a static investment analysis that determines NPV from a series of future cash flows and a discount rate. The cash flows will include revenues from WEC production and transmission to the wholesale electricity market. The electricity market is known to be volatile, so we model the uncertainty as a stochastic process to determine a distribution of cash flows, and subsequently a distribution of values. This financial valuation model also includes salient elements of a proposed WEC design and the cost impact of maturing it to Technology Readiness Level (TRL) 9 when the designs may be implemented at scale. This study then applies the theory of real options, or options on real assets, to model the optimal decisions of future staged investments to higher Technology Readiness Levels (TRL) and capital expenditures (CapEx) should be undertaken.

2. Materials and Methods

2.1. Energy Price Forecast with Uncertainty

We obtained data on wholesale market data for energy prices to support cash flow and volatility inputs needed for real option valuation. We used data from the Nordpool group (2024), which has a long history on promoting price transparency. We obtained monthly N2EX day ahead auction prices from 108 months from March 2014 to December 2023. No data was available for the nine months of January-September, 2021, and the time series started in March 1014. A service specialist at the NordPool group indicated that Brexit was the cause for this interruption in data. However, our key conclusions were unaffected by this data interruption. Considering the break in this data in 2021, the 2014-2020 pricing data appears stationary, while the late 2021-2023 data is highly volatile and appears to be returning to a price of approximately 100 Euros per MWh. This time series appears in Fig. 1. The higher prices and volatility in late 2021 to the end of 2023 could be caused by the combination of post-pandemic effects and other regional economic shocks disrupting regional energy markets in the region, as suggested by Lu et al (2024).

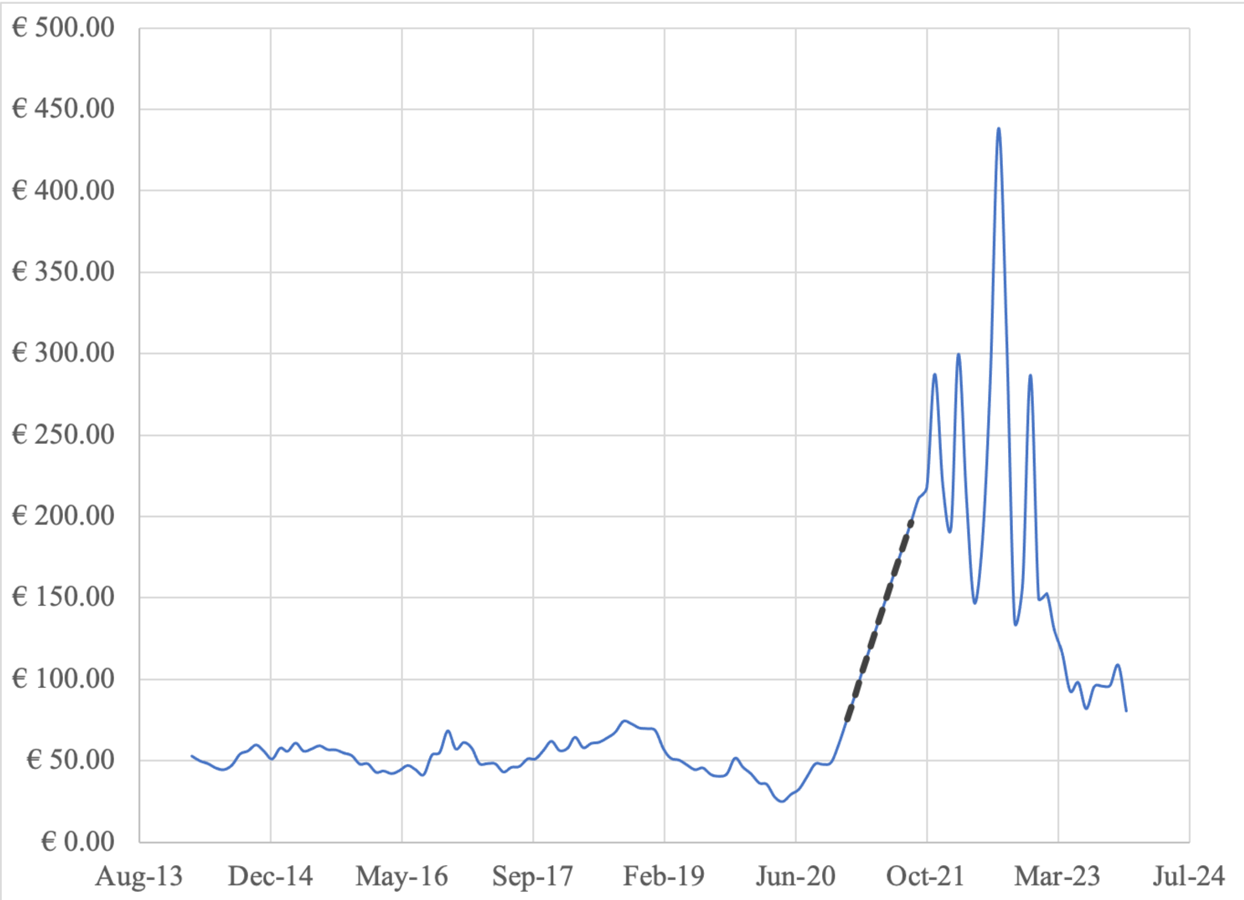

Figure 1. Time series of UK wholesale electricity prices.

To begin, we investigate the distribution of monthly returns r determined by the log of relative price, or

$$r = \ln\left(p_t/p_{t-1}\right), \quad (1)$$

where p_t is the current month price and p_{t-1} is the previous month price. The histogram of these returns appears in Fig. 2. Since the returns appear normal, we assume that prices can be modeled with a random walk, or more specifically as geometric Brownian motion (GBM), as suggested by Fama (1965) and used by Black and Scholes (1973).

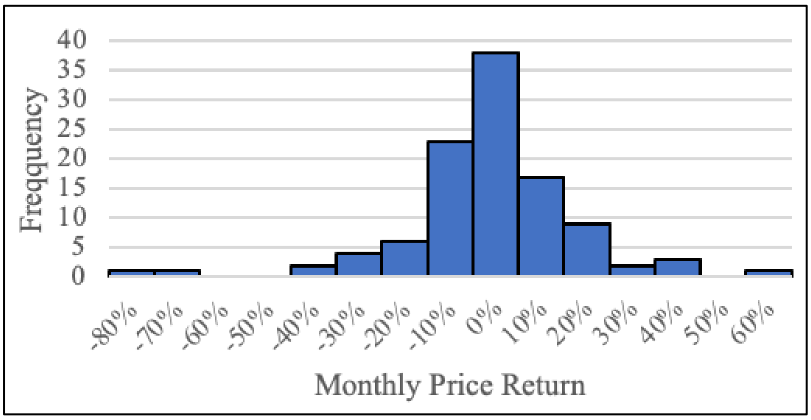

Figure 2. Histogram of monthly returns of UK wholesale electricity prices, 2014 – 2023.

To calibrate our GBM stochastic process to model price, we need to estimate growth and volatility terms for our stochastic differential equation in Eq. (2).

$$dP = \mu P dt + \sigma P dz, \quad dz = \epsilon\sqrt{dt}, \quad \epsilon \sim N(0,1) \tag{2}$$

Here, dP is the change in price P, μ and σ are the growth rate and volatility, and dz represent the standard Wiener process. The last term in Eq. (2) is the random variable from the standard normal distribution. This formulation is similar those found in Dalbem, et al (2014) and Dixit and Pindyck (1994).

We estimate the growth rate from a nonlinear curve fit of the equation

$$P_t = a_0 \mathrm{e}^{rt}. \tag{3}$$

Taking the natural log of both sides and simplifying yields the linear equation

$$\ln(P_t) = \ln(a_0) + rt. \tag{4}$$

So, the slope of the natural log of price will yield the estimated growth rate r. Then, the volatility s is estimated as the standard deviation of monthly returns. The growth rate is annualized by multiplying it by 12, and the volatility is annualized by multiplying it by $\sqrt{12}$, as supported in Benninga (2014). Consequently, using all the pricing data available yields annualized growth and volatility of 13.0% and 64.3%, respectively.

At this point, we didn't believe that the future energy markets would support these values for a GBM forecast, given the economic shock that the wholesale electricity markets withstood in 2021-2023. We can see this by examining a monthly rolling volatility over 12-month periods. As shown in Fig. 3, we see that prior to 2021, values were between 20% and 60%, and that current volatility appears to be returning to this range. So, for our forecasting of price and the real options analysis to follow, we assume a volatility of 40% as a baseline value.

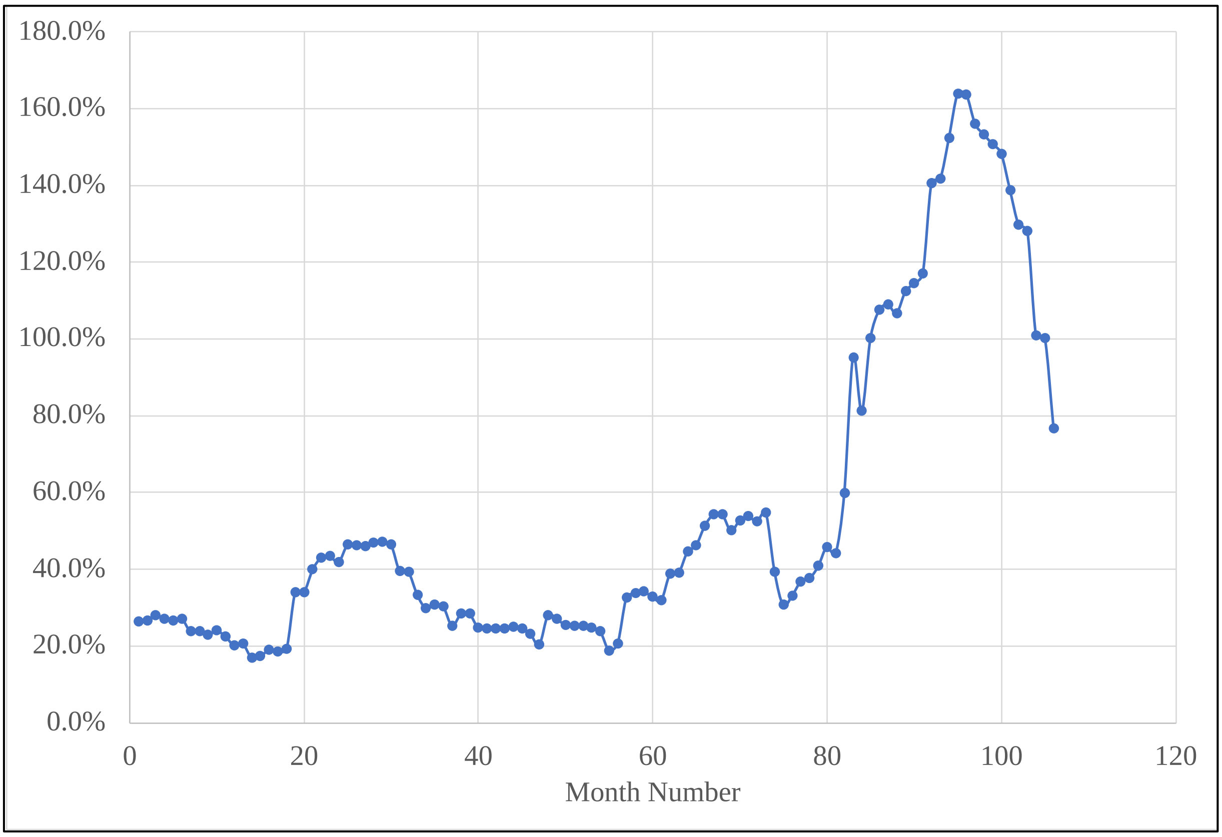

Figure 3. 12-month rolling annualized volatility, 2014-2023.

Also, assuming wholesale electricity growth rates will likely return to lower values, we set our value for annualized price growth to 6%. Such a value is subjective, and could vary based on economic conditions like inflation, energy policies, technological advancements and global energy markets. Nevertheless, it does capture wholesale nominal price increases likely necessary to include these effects, similar to the assumptions made by Schwartz and Smith (2000) for processes with short-term and long-term components, or jump processes described by Winston (2008). Using these values, our expected forecast with upper and confidence intervals at a 10% and 90% level appears in Fig. 4. In the pro forma cash flow model in the next section, we will use the mean price forecast to determine our expected cash flows from operating a WEC system, similar to the approach used by Hahn et al (2018).

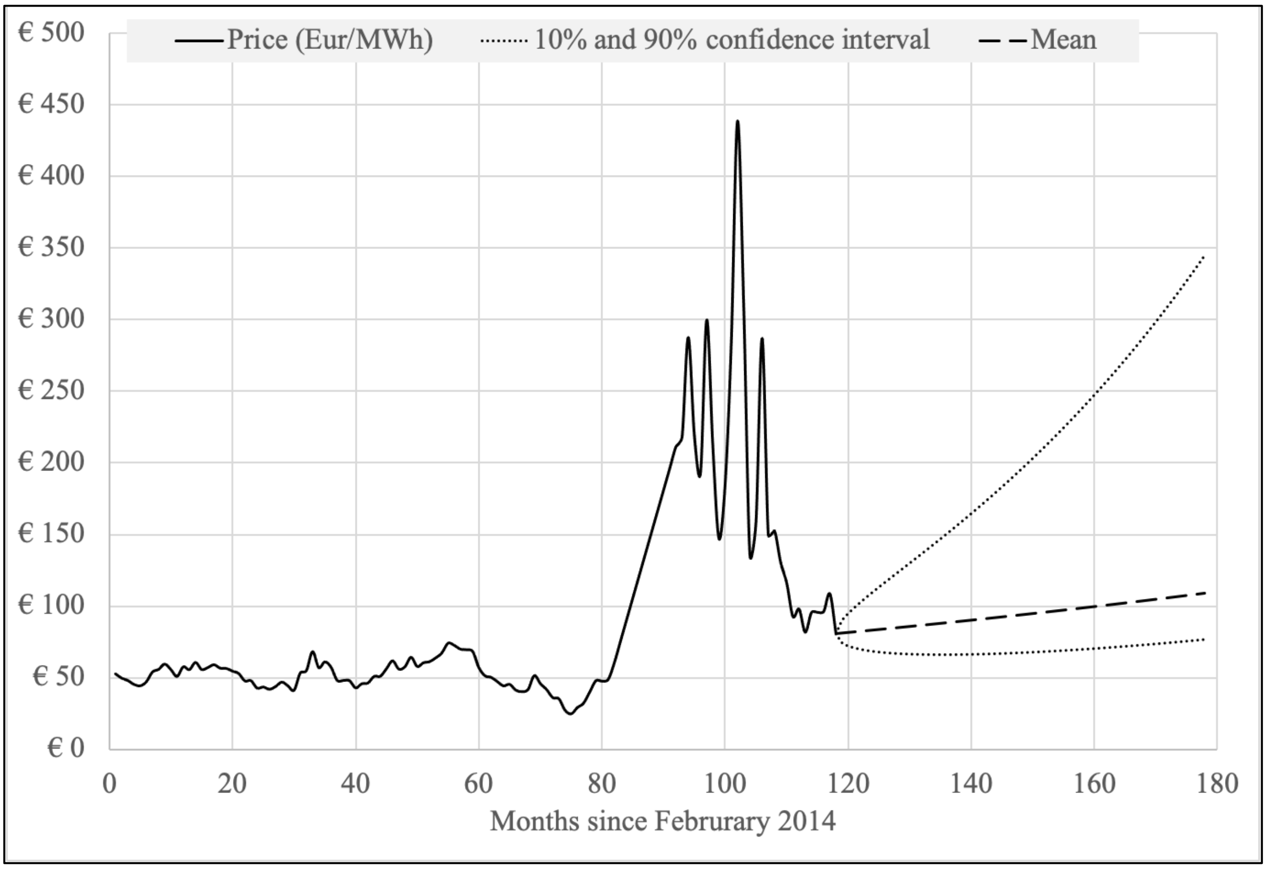

Figure 4. GBM process forecast for wholesale electricity prices.

2.2. Site Selection and Annual Energy Production

Under the Market Asset Disclaimer suggested by Copeland and Antikarov (2003), we next developed a baseline model as our WEC system project without optionality. Doing so provides us with a complete market to support our real options analysis in the following section. We begin with modifying the Annual Energy Production (AEP) equation from Section 1.4.2 of Pecher and Kofoed (2016) to a Monthly Energy Production (MEP) estimate. AEP can be found based on the equation:

$$AEP = \sum_{i=1}^{12} MEP_i, \tag{5}$$

where MEP_i is the Monthly Energy Production for month i, where I = 1 for January, i=2 for February, etc. So, we state that

$$MEP = P_{wave} \times width_{absorber} \times \eta_{w2w} \times availability_{monthly} \times hours_{monthly} \times n_{WEC}\ . \tag{6}$$

Here, P_{wave} is wave power in kW/m and is location dependent. The next term $width_{absorber}$ is the width of the WEC absorber in meters, and can vary based on the chosen WEC design. The third term η_{w2w} is the wave-to-wire efficiency as a percentage and is a weighted average over all wave conditions. The next terms $availability_{monthly}$ and $hours_{monthly}$ are the percent of time the WEC is producing each month and the total number of hours per month, respectively. Lastly, the term n_{WEC} represents the number of WEC devices operating throughout the project's lifecycle. This estimate is considered reasonably accurate at $\pm 50\%$ by Pecher and Kofoed (2016), which will be explored in the sensitivity analysis in the following section.

By using the variable $hours_{monthly}$, we include the effect of seasonality shown in O'Connell and Furlong (2021) and Rizaev et al. (2023). So, we can increase availability during peak months by deferring periodic maintenance until times of the year with lower wave power. We show below that the strongest wave power occurs in the winter months of December, January and February and the weakest wave power occurs in the summer months of June, July and August, so will assume higher availability in the winter months and lower availability during the summer months.

We next employ the long-term average of wave power from 42 years of Copernicus data[1]. The wave power P_{wave} describes energy transmission by waves and encompasses both the significant wave height H_s and the energy period T_e. Assuming irregular waves and deep water per unit crest length, P_{wave} is given by:

$$P_{wave} = \frac{\rho g^2}{64\pi} H_s^2 T_e \approx 0.49 H_s^2 T_e \ (kW/m) \quad (7)$$

where ρ is the sea water density (~1025 kg/m³), and g is the gravitational acceleration.

However, the sites we chose represent intermediate and deep waters, so an advanced calculation method was used. This method is formulated as a general wave energy assessment equation (GWEAE) and is defined by Liang et al (2017).

$$P_{wave} = \frac{\pi \rho g D H_s^2}{16 T_e} \left[\frac{1}{\mu} + \frac{2}{\sinh 2\mu}\right] \quad (8)$$

Here, an explicit approximation of the linear dispersion relation μ is equal to Beji (2013). The details can be also found in Rizaev et al (2023). The variable D is the water depth, which is estimated based on the numerical bathymetry model in Saulter (2021).

Table 1 shows the values for P_{wave} at three locations around the United Kingdom and represent annual seasonal wave power from the 42 years of monthly Copernicus data. We assume these seasonal long-term averages will remain time invariant for purposes of our pro forma cash flow model.

Table 1. Average Seasonal Wave Power for three sites considered in Fig. 5, representing low, moderate and high potential for a commercial wave energy system.

	Site	**Winter** (Dec., Jan., Feb.)	**Spring** (March, April, May)	**Summer** (June, July, August)	**Autumn** (Sep., Oct., Nov.)
P_{wave} (kW/m)	A	109.634	48.3112	17.7887	55.9195
	B	84.3359	38.7219	12.5485	46.5122
	C	18.8204	10.389	4.5571	13.5729

Sites A, B and C, along with the annual mean wave power appears in Fig. 5. The wave power estimation is based on an analysis forecast numerical wave model[2] from the Copernicus Marine Environment Monitoring Service (CMEMS). The location considered for site A is a longitude of 8.5152°W and latitude of 55.9189°N, site B is a longitude of 2.4849°E and latitude of 62°N, and site C is a longitude of 1°W and latitude of 56.8919°N. From Fig. 5, we see that similar to the seasonality of wave power shown in Table 1, site A has the highest wave power, followed by site B. Site C has the lowest wave power. These sites were chosen to represent best, moderate, and worst-case wave power locations to operate a WEC system in locations in relatively close proximity to the UK power grid.

[1] https://data.marine.copernicus.eu/product/NWSHELF_ANALYSISFORECAST_WAV_004_014/description

[2] Product NORTH-WESTSHELF_ANALYSIS_FORECAST_WAV_004_014

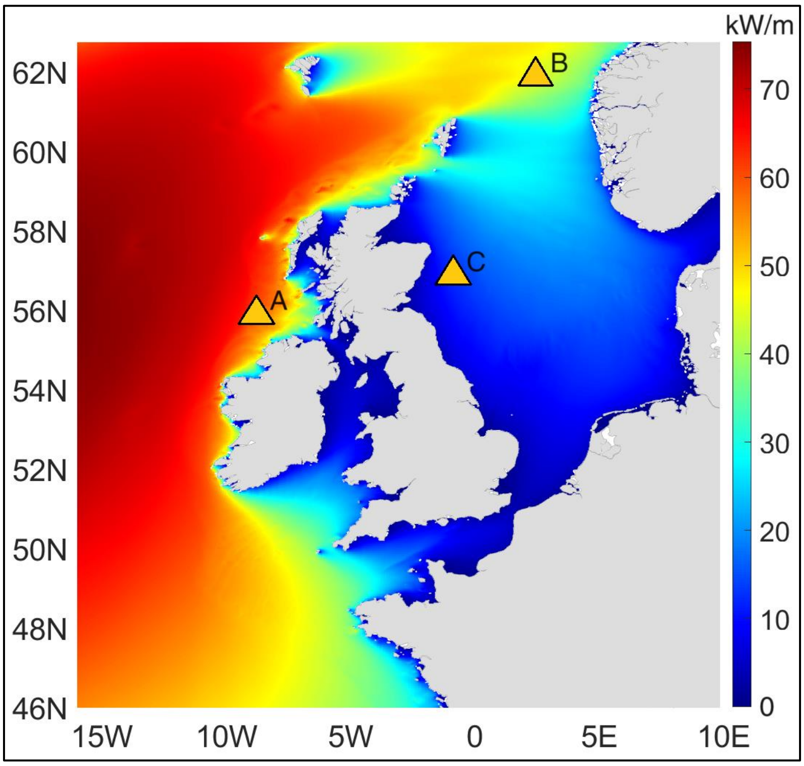

Figure 5. Climatological annual mean wave power, 1980-2021.

The second, third and fourth variables in our MEP model in Eq. (6) are set according to Table 2.

2.3. Reference Design of a WEC from a TALOS Design

Table 2. Design parameters based on page 6 of Pecher and Kofoed (2016) and TALOS design from Sheng and Aggidis (2024).

Design Parameter	Value
$width_{absorber}$	30 m
η_{w2w}	0.2
$availability_{monthly}$	[Dec, Jan, Feb, Mar, Apr, May, Jun, Jul, Aug, Sep, Oct, Nov.] = [0.99, 0.99, 0.99, 0.95, 0.95. 0.95, 0.9, 0.9, 0.9, 0.95, 0.95, 0.95]
n_{WEC}	25

Note that the width of the absorber at 30 m is consistent with the TALOS WEC design as shown in Sheng and Aggidis (2023) and was used to measure wave conditions at the EMEC test site, Billia Croo, Scotland. The specific TALOS design used here is an optimized TALOS, the tailless TALOS, from Sheng and Aggidis (2024), appears below in Fig. 6. The overall annual wave energy production, with the applications of an energy efficiency of 75% from the captured wave energy to electricity and a rated power of 625kW, yields a corresponding capture factor of 0.243. While this production is about half the value for site B, and was chosen so that the test devices would not be subject to more severe wave conditions, the value for η_{w2w} in Table 2 is a reasonable estimate which we expect to hold in a commercialized system under more severe wave conditions like those for site A and B.

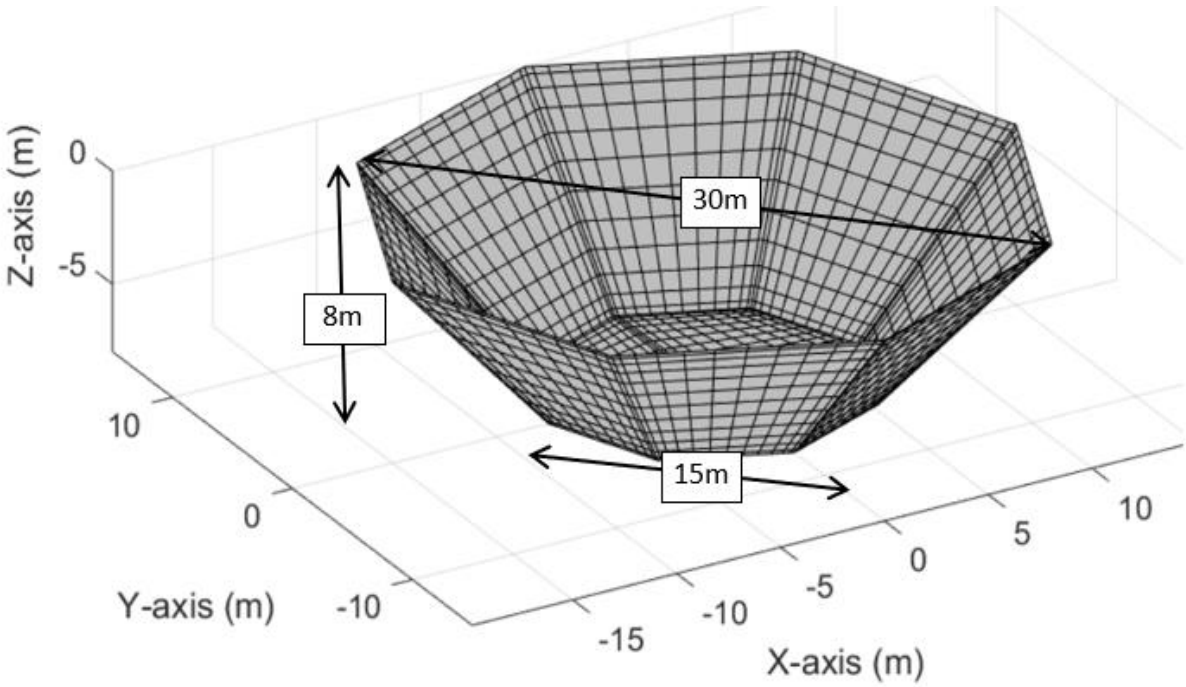

Figure 6. The tailless TALOS (displacement: $2969m^3$).

The availability design parameter in Table 2 includes seasonal adjustments for maximize winter season energy conversion and defer maintenance to the summer season. It also includes the need for the WEC system to enter survival mode during extreme weather events.

Using the values from Table 2, we determine 12 monthly MEP and corresponding AEP for site A, B and C. As previously noted, the values in Table 3 are subject to an estimation error of $\pm 50\%$, as indicated by Pecher and Kofoed (2016).

Table 3. Annual Energy Production from sites A, B, and C.

Site	AEP (MWh/year)	AEP per WEC (MWh/year)
A	73,005	2,920
B	57,394	2,296
C	14,869	595

2.5. Estimating Project Capacity

We assume the TALOS design is at a Technology Readiness Level (TRL) 6 in the following section to estimate likely costs. Following the International levelized Cost of Energy for Ocean Energy Technology (2015), AEP is defined as

$$AEP = capacity * F * availability * 8760, \quad (9)$$

where 8760 is the number of hours per year, found by 24 hrs/day * 365 days/year. Here, *capacity* is the project capacity, F is the capacity factor, or alternatively called the load factor by UK report from 2020 from the department of Department for Business, Energy & Industrial Strategy. From this UK report, $F * availability$ = 30%. We can solve for the system capacity as

$$Capacity = AEP/(F * availability * 8760) \quad (10)$$

Then, the capacity of the projects operating at sites A, B and C from Table 3 are approximated as 27.8 MW, 21.8 MW and 5.7MW, respectively.

3. Cash Flow and Real Options Model

3.1. Underlying Model

We next infer the following cost parameters to complete our static financial model without optionality. We started with CapEx per AEP using Table 9 from Guo et al (2023), which listed values between 0.041 and 0.455. We chose the largest of these values to avoid the use of investment steps these authors used to reduce this expense, which is already inherit in the real option models to follow. The value for CapEx per AEP is also critical because we assume annual OpEx is a fixed proportion shown in the second row of Table 4, which is supported in the literature by de Andrés et al (2017), Tan et al (2021), Biyela and Cronje (2016), Stansby et al (2017), Gaunche (2014), de Andrés et al (2016), and Lavidas and Blok (2021).

Table 4. Baseline cost parameters and their sources.

Cost Parameter	Values	Source
CapEx per AEP (Euro/KWh)	€ 0.455 / KWh	Guo et al (2023), p. 24
OpEx/MWh, Year 1	5 to 15% of CapEx	Guo et al (2023), p. 15
TRL 6 to 7	€ 10 to 15M	Pecher and Koefoed (2016), p. 88
TRL 7 to 8	€ 10 to 15M	Pecher and Koefoed (2016), p. 88
TRL 8 to 9	€ 20 to 100M	Pecher and Koefoed (2016), p. 88
Discount Rate	8 to 10%	Guo et al (2023), p. 18.
Operating Years	20 to 50	Guo et al (2023), p 18.

For our other baseline cost estimates, we assume midpoint values from Table 4. So, we set OpEx/MWh for Year 1 to 10%, TRL increases occur at the midpoint of their cost range, discount rate is 9%, and the system operates for 35 years with no salvage value or decommissioning cost. We also ignore the implication of taxes, tariffs and depreciation.

3.2. Research, Development, CapEx and OpEx Timelines

The timeline for the financial model includes sequential investments to improve TRL, followed immediately by CapEx, then by OpEx. The research and development phase for each TRL improvement lasts one year. So, we begin assuming the TALOS design is at a TRL 6. We invest today, year 0, to move the technology from TRL 6 to 7. In year 1, we invest again to move the technology from TRL 7 to 8. Lastly, in year 2, we invest to move the technology from TRL 8 to 9. Then, in year 3, we invest for CapEx, to produce the WEC units and deploy them, at a present value of PV_{CapEx}. Lastly, in year 4, we begin operation of the WEC system and selling electricity into the wholesale market, producing a present value in today's dollars of $PV_{underlying}$.

So, the project's NPV is expressed as

$$NPV = -PV_{TRL} - \frac{PV_{CapEx}}{(1+r_d)^3} + \frac{PV_{underlying}}{(1+r_d)^4}, \qquad (11)$$

where r_d is the project's discount rate, and

$$PV_{TRL} = PV_{6-7} + \frac{PV_{7-8}}{(1+r_d)} + \frac{PV_{8-9}}{(1+r_d)^2}\ . \qquad (12)$$

Using the mid-point values for TRL increases and the discount rate shown in Table 4, we find that $PV_{TRL} =$ € 74.5M. We then determine the CapEx and the annual OpEx for sites A, B and C, with results appearing in Table 5. To include increasing future operational costs, we set the OpEx annual growth rate of 4%. To determine the net cash flow for each year, we assume first year operations generate revenue at a rate of €100/MWh, that grows at a rate of 6% per year. Subtracting the Annual OpEx from these revenues, and discounting the cash flows at 9% yields a $PV_{underlying}$ as shown in the third last column of Table 5. Combining Eq. (11) and (12) then produces the NPV in the last column of Table 5.

Table 5. Costs, operational value, and *NPV* estimates for sites A, B, and C. All values in Euros (€).

Site	PV_{TRL}	PV_{CapEx}	$PV_{underlying}$	*NPV*
A	74.5M	33.2M	105.1M	-25.7M
B	74.5M	26.1M	82.6M	-36.1M
C	74.5M	6.77M	21.4M	-64.5M

As the results in Table 5 show, negative NPVs occur for all the sites. So, we can characterize these all as out-of-the-money call options. But, prior to investigating the option value in this project, we perform a sensitivity analysis in the next section to see which factors in this deterministic model have the greatest impact on NPV.

To validate our cost assumption, we note that the combination of TRL and CapEx costs in Table 5 sum to approximately €100 M for sites A and B. For a system capacity of approximately 25 MW, estimated in the previous section, and using the total CapEx Factor of €4 M / MW from Table 7 of Ocean Energy in the European Union (2022) for systems with capacity greater than 20 MW, we confirm that this €100 M total investment is an appropriate cost estimate at this stage in the TALOS design. Nevertheless, given the uncertainty of these cost estimates, the following section conducts a detailed sensitivity analysis.

3.3. Sensitivity Analysis

To conduct a sensitivity analysis, we evaluated site A and varied each of the following variables individually. The baseline values used previously, along with high and low values, appear below in Table 6.

Table 6. Low, baseline and high values for sensitivity analysis. All values in Euros (€).

Variable	Low	Baseline	High
P_wave factor	0.5	1.0	1.5
Expected growth rate of wholesale electricity prices	3%	6%	7.5%
Discount rate	8%	9%	10%
CapEx per AEP (Euro/KWh)	0.2275	0.455	0.6825
OpEx/MWh for Year 1	22.75	45.5	68.25
OpEx growth rate	2%	4%	6%
TRL 6 to 7 (M Euro)	10	12.5	15
TRL 7 to 8 (M Euro)	10	12.5	15
TRL 8 to 9 (M Euro)	20	60	100

We then estimated the NPVs for each of these combinations and sorted them from largest absolute change to smallest. So, the top row of Table 6 shows which variable has the largest impact of NPV, and the last rows shows the variable with the smallest impact on NPV.

Table 7. NPV sensitivity to model variables, sorted largest to smallest absolute change, site A.

Variable	*NPV* Low	*NPV* Baseline	*NPV* High
TRL 8 to 9 (M Euro)	9	-25.7	-59.3
Expected growth rate of wholesale electricity prices	-63	-25.7	2.8
CapEx per AEP (Euro/KWh)	6.9	-25.7	-58.2
P_wave factor	-50	-25.7	-1.3
OpEx/MWh for Year 1	-5.9	-25.7	-45.4
Discount rate	-12	-25.7	-36.2
OpEx growth rate	-17	-25.7	-38

TRL 6 to 7 (M Euro)	-23	-25.7	-28.2
TRL 7 to 8 (M Euro)	-23	-25.7	-28

Table 7 shows that a WEC project's valuation is most sensitive to TRL 8 to 9, growth rate of wholesale electricity prices, and CapEx. However, the project's NPV is least sensitive to TRL increases from 6 to 7 and 7 to 8. This latter result supports our findings in the next section indicating that the relatively low cost of this research and development phase having little effect on the overall project's profitability. We expect to see a similar trend for sites B and C, so do not include them here. Instead, we focus the next sections on the option value that may be part of a project like this one. We also note that, in nearly all cases, the high NPV values usually remain negative. So, in the next section, we explore if (or when) there is enough option value to change the baseline NPV from negative to positive, by modeling the problem like an out-of-the-money call option.

3.5. Risk Neutral Valuation of the Option to Increase TRL and Operate the WEC System

We next implement a decision tree approach with a binomial lattice to model the underlying uncertain cash flows using a risk-neutral valuation methodology. This compound option is similar to the compound option found in Copeland and Tufano (2004) and DiLellio (2022), where prior investments were required before production and associated cash flows could occur to yield $PV_{underlying}$. The figure below shows the structure of the decision tree associated with this compound option using the commercial decision analysis package DPL® from Syncopation software.

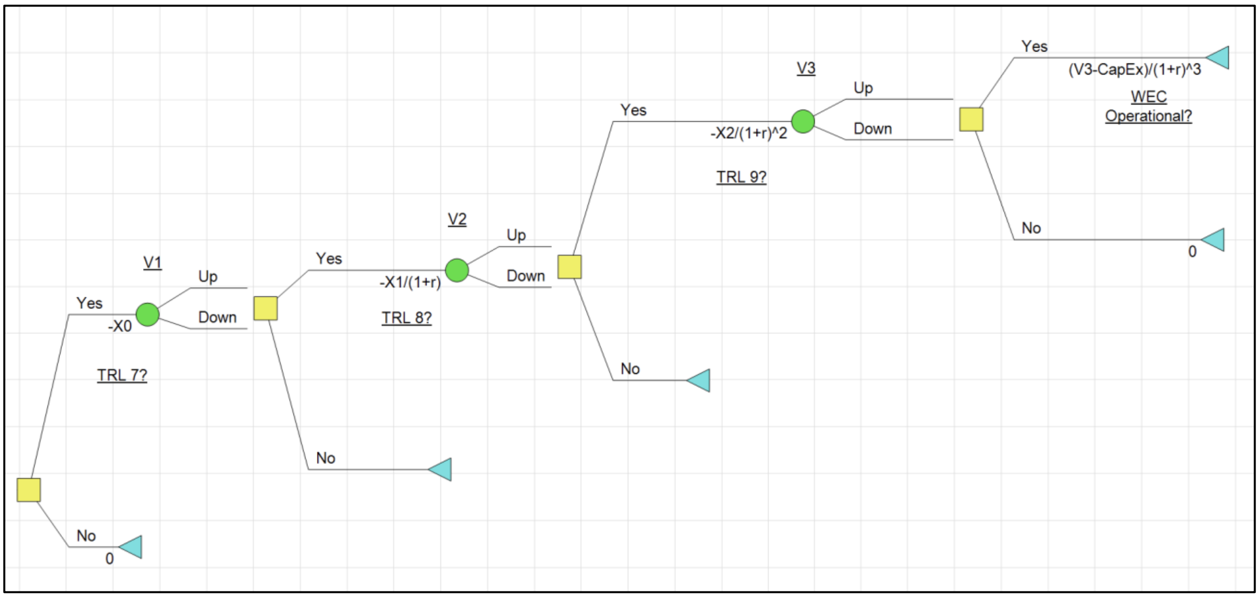

Figure 7. Decision Tree for Compound Option.

In Fig. 7, the project starts today with an investment of X0 to reach a TRL 7. If this investment is not made, then the project is over and the NPV is 0. However, if the TRL 7 investment is made, then TRL 7 is achieved in one year. The next decision is whether to invest X1 Euros to reach TRL 8. If this next investment is made, another year passes. Otherwise, the project ends with an NPV of -X0. The final investment to reach TRL 9 must be decided upon at a cost of X2 Euros. If TRL 9 is not pursued, then the project's NPV is -X0 – X1/(1+r), where r is the risk-free rate.

If the TRL 9 investment is made, another year passes, and now we have the option to invest CapEx to build the system, which produces uncertain cash flows V3 based on the value of the underlying shown in Table 5. Fig. 8 shows how a non-recombining binomial lattice, based on Cox et al (1979) models the uncertainty in $PV_{underlying}$, assuming a risk-free rate r equal to 5%. The underlying lattice values were found based on up and down factors (u and d), and associated risk-neutral probabilities (p), are shown by Cox et al (1979) with Δt=1 year and $\sigma = 40\%$.

$$u = e^{\sigma}, d = \frac{1}{u}, p = \frac{1+r+d}{u-d} \quad (13)$$

While Fig. 8 is for site A, similar models for the underlying project's uncertain values were produced for sites B and C, but not included for sake of space. Also, note that Cox et al (1979) generate a recombining lattice, where *n* periods produce *n+1* unique terminal values. In this example, the three-period model has four unique terminal nodes. However, using a decision tree provides greater flexibility and doesn't assume terminal nodes re-combine at the small additional cost of computational time. So, for this 3-period model, there are eight terminal nodes. Nevertheless, the computational results are unaffected. Lastly, the up and down values shown here correspond to a risk-neutral valuation approach, so that future values may be discounted at the risk-free rate. Also, risk-neutral valuation does not require additional future uncertainty states after the decision to make the WEC operational since there were no later downstream decisions in the decision tree in Figure 7.

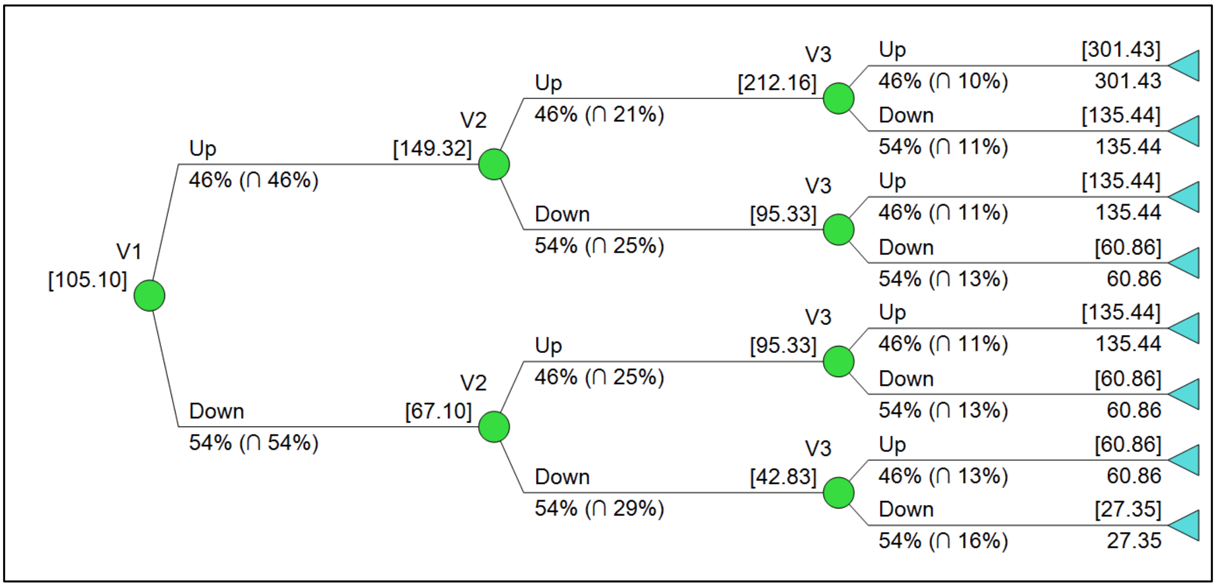

Figure 8. Non-recombining lattice to model the uncertain value of the underlying projects cash flows for site A.

As Fig. 8 shows, the uncertainty of the future wholesale electricity prices at a 40% volatility could yield a present value of the underlying as high as 323 M Euros, or as low as 29.3 M Euros once operations begin. Then terminal nodes also show the conditional probabilities to reach outcome, which provides a discrete approximation of a log-normal distribution.

4. Results and Discussion

Baseline Model Valuation with Option to Deploy

Applying this underlying uncertainty to our decision tree in Fig. 7 produces a positive NPV for site A and B, but not for C. These values are summarized in Table 8.

Table 8. Expected NPV for WEC system with optionality.

Site	Expected NPV
A	€ 12.6 M

B	€ 1.17M
C	€ 0.0 M

Details of the decision tree for sites A appears in Fig. 9 and site B in Fig. 10. We exclude the policy tree for site C, as it has no value. That means, there is no option value for site C and there are no conditions where site C should be pursued for investment. Put another way, if site C were the only site available for investment, neither investing to achieve higher TRLs nor CapEx investments should be made.

However, sites A and B do have significant option value. They also offer insights into how these optimal decisions were obtained. In both cases, it was always optimal to invest in reaching TRL 7. However, if wholesale electricity prices and their corresponding expectations on future cash flows are low, then it is never optimal to pursue TRL 8. After the TRL 8 investment decision, optimal decisions change for site A and site B.

For site A, it is always optimal to invest in TRL 9, then build and operate the WEC system at site A for the next 35 years. There is a 46% chance of making the investment to reach TRL 8, as shown in the "Up" branch after the decision to invest in TRL 7 is made. Ultimately, the WEC system has positive NPVs in three out of the four uncertain project values. As shown in the upper right portion of Fig. 9, there is a 10% chance of an NPV of 193.9 M Euros, and a 22% chance of an NPV of 27.9 M Euros. And, there is a 13% chance of a -46.7 M Euro NPV. While this last outcome is not preferred, it is statistically better than simply avoiding the CapEx and OpEx, and not deploying a WEC system to produce electricity for the wholesale markets.

However, at site B, conditions are less favorable. If the value of the underlying goes down in the 2nd year after going up in the first year, then the project is no longer worth pursuing, so investments in TRL 9, CapEx and OpEx will not be made. However, if conditions are favorable at site B after both the 1st and 2nd year, then the investments in TRL 9, CapEx and OpEx should be made, thereby producing a series of cash flows for the next 35 years.

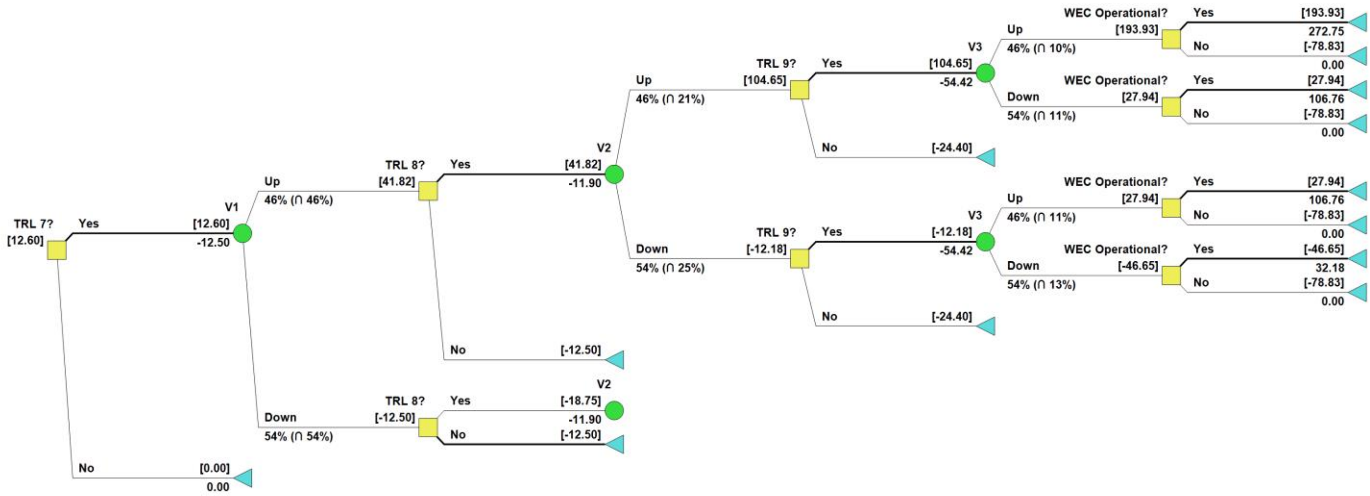

Figure 9. Policy Tree for site A with an expected NPV of 12.6 M Euros.

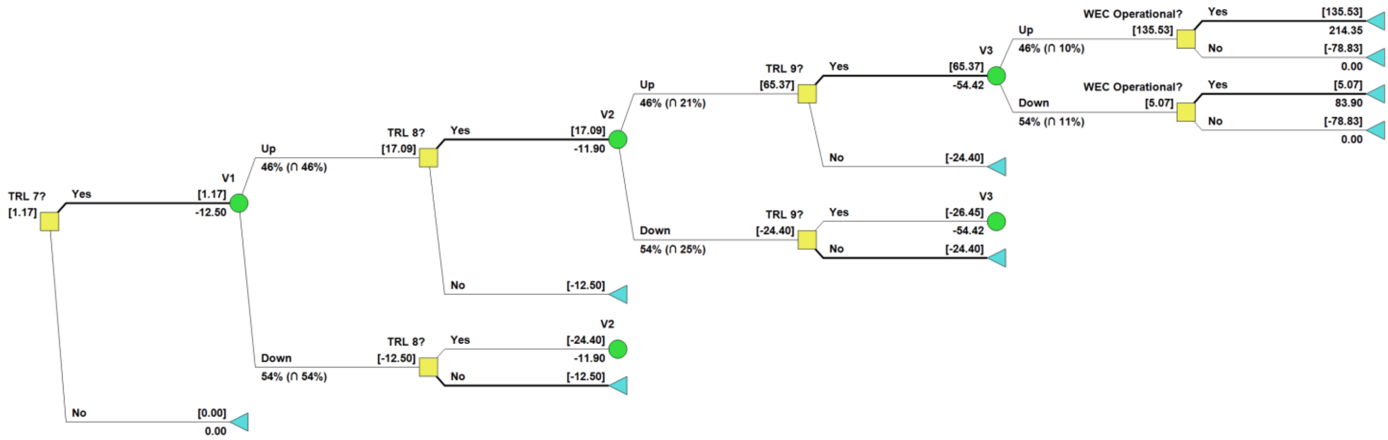

Figure 10. Policy tree for site B with an expected NPV of 1.17 M Euros.

5. Conclusions

This analysis demonstrates that an investment in increasing the TRL of a WEC system, fielding and operating it is similar to a financial out-of-the-money compound call option whose value depends on future electricity prices. Based on a site survey of wave energy expectations, we show that all three sites produce negative NPVs without optionality, indicating they are not worthy of investment. Our sensitivity analysis largely supports this conclusion. However, when the investment problem is considered as a compound option, we see that two of the three sites can produce a positive expected NPV when future wholesale electricity prices are higher than expected. This simple but demonstrative analysis shows how often such payoffs may occur as a proxy for investor risk. This work also shows that investors should consider probabilistic estimates of value from an optimal decision framework enabled by real options analysis when considering investments that are not yet at TRL 9. Future work in this area could long-term secular trends of wave energy, as recently examined by Chen (2024) and Liu et al (2024), as these types of energy systems will likely operate for many decades. Similarly, as the TRL increases, wave power estimation error can be decreased by using a power matrix suggested by Babarit et al (2012) and Guillou et al (2020). Lastly, one can determine Levelized Avoided Cost of Energy (LACE) and Levelized Cost of Energy (LCOE) by applying a framework proposed by Beiter et al (2017) to align with metrics utilized by government agencies interested in public-private partnerships with private capital investors.

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