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Article

Optimal life extension management of offshore wind farms based on the modern portfolio theory

Baran Yeter [1] and Yordan Garbatov [2,*]

[1] Centre for Marine Technology and Ocean Engineering (CENTEC), Instituto Superior Técnico, University of Lisbon; baran.yeter@centec.tecnico.ulisboa.pt
[2] Centre for Marine Technology and Ocean Engineering (CENTEC), Instituto Superior Técnico, University of Lisbon; yordan.garbatov@tecnico.ulisboa.pt
* Correspondence: yordan.garbatov@tecnico.ulisboa.pt

Abstract: The present study aims to develop a risk-based approach to find optimal solutions for life extension management for offshore wind farms based on Markowitz's modern portfolio theory, adapted from finance. The developed risk-based approach assumes that the offshore wind turbines (OWT) can be considered as cash-producing tangible assets providing positive return from the initial investment (capital) with a given risk attaining the targeted (expected) return. In this regard, the present study performs a techno-economic life extension analysis within the scope of the multi-objective optimisation problem. The first objective is to maximise the return from the overall wind assets, while the latter aims to minimise the risk associated with obtaining the return. In formulating the multi-dimensional optimisation problem, the life-extension assessment considers the results of a detailed structural integrity analysis, free-cash-flow analysis, and probability of project failure, local and global economic constraints. Further, the risk is identified as the variance from the expected mean of return on investment. The risk-return diagram is utilised to classify the OWTs of different classes using an unsupervised machine learning algorithm. The optimal portfolios for the various required rate of return are recommended for different stages of life extension.

Keywords: Offshore wind; life extension; modern portfolio theory; unsupervised machine learning; monopile; risk management

1. Introduction

Offshore wind turbine (OWT) structures approaching the end of their service lives are in a structural condition for extended use, mainly due to the conservative design philosophies and operation policies adopted by the oil & gas offshore industry. In this regard, the offshore wind industry is searching for a reliable guideline for certification assuring a structural capacity above the permissible limit within the desired extended service life at minimal operational cost. Such policies can only be achieved by comprehensive life extension assessment encapsulate both technical and economic analysis. The techno-economic analyses for life-cycle extension projects must incorporate structural health monitoring data, detailed structural integrity assessment, condition-based maintenance, and detailed financial analysis. Furthermore, developing a guideline that helps the life-extension certification requires a multi-disciplinary approach involving state-of-the-art modelling, analysis, and prediction techniques using the experience gained from the research centred on design and life-cycle optimisation of OWTs.

To tackle the challenges mentioned above and contribute to the current state of the art, the present work aims to develop a novel approach in finding optimal solutions for life extension management for a multi-unit offshore wind farm based on Markowitz's modern portfolio theory, adapted from finance. The novel approach is developed based on the assumption that offshore wind turbines can be considered a cash-producing tangible asset that provides a positive return from the initial investment with a given risk attaining the targeted return. In this regard, the present study performs a techno-economic life extension analysis within the scope of the multi-objective optimisation problem. The first objective is to maximise the return from the overall wind assets, while the latter aims to minimise the risk associated with obtaining the return.

The modern portfolio theory, MPT, is created by Markowitz [1] based on the premise that the investors are risk-averse, and they aim to maximise the expected return from the selection of the possible investment options. MPT pioneered the quantitative financial analysis by suggesting the investment selection is a quadratic optimisation problem with linear constraints to maximise the overall return and minimise the risk [2].

This multi-objective optimisation problem results in constructing an efficient frontier [3]. The MPT was later modified to build a generalised theory by Sharpe [4] and Treynor [5,6] for the capital asset pricing model to assist with investment decision-making. The modern portfolio theory and capital asset pricing model provided a decent way of looking at the equilibrium between the risky assets with a different expected return and a tool for measuring the performance of available investment strategies.

The modern portfolio theory is built on many assumptions. However, one assumption draws more reaction than the others: risk can be measured as the dispersion of dataset of returns relative to its mean value, in other words, standard deviation. Maier-Paape and Zhu [7,8] reviewed the definition of the risk within the context of modern portfolio theory, its limitations, objections and some alternative risk measures.

The importance of the risk on the offshore wind projects and risk mitigation by diversification addressed in earlier studies. In this regards, Green and Vasilakos [9] suggested that it might prove to be economical to build an international offshore grid connecting wind farms belonging to different countries that are situated close to each other. Levitt*, et al.* [10] highlighted those risk policies and finance structure also have a strong influence on wind power prices, and the wind prices were justifiably scattered depending on the riskiness of the project as they are categorised from high to low risk as first of a kind, global average, and best recent values. Further, Blanco [11] stated that de-regularisation of the power market would lead to risk exposure to the profitability of the investment. The studies mentioned above identified some of the critical elements for financing and managing the life cycle that needs to be accounted for in the multi-disciplinary risk-based life extension analysis.

Although Markowitz's modern portfolio theory was initially developed for financial assets, there has been quite an interest in applying the theory for the non-financial assets because it allows for an overall assessment of portfolio consisting of asset groups of different risk levels instead of analysing the portfolio asset individually. Further, it allows for a minimisation of risk through diversification, which is one of the main premises of the MPT.

Chaves-Schwinteck [12] provided comprehensive research on the applicability of modern portfolio theory to wind farm investments. The study was based on a critical review of the already published works that mainly focused on risk mitigation through geographical diversification (different wind farm location) [13,14] and renewable energy asset diversification (a portfolio of solar, wind, and hydro) [15]. Chaves-Schwinteck [12] underlined the difference in the definition of risk between a long-term infrastructure project and a short-term financial investment. However, the research also acknowledged that using appropriate diversification MPT can be a good tool for risk mitigation strategy for wind farm investment by optimising the wind regime and technical risk details of the operation of a wind farm. Besides, a number of studies have attempted the application of the modern portfolio theory to take advantage of the power of diversification to mitigate the overall project risk and optimise the portfolio of energy production assets [15-22].

In terms of the offshore wind industry, Cunha and Ferreira [22] presented a study in which diversification can help reduce the variability in energy production, which aimed to assist the decision-making process related to the geographic location of offshore wind investments. Thomaidis et al. [23] also stated the advantages of power mixes compared to single-site installation. The result of the study highlighted the benefits of diversification by showing that the sites with high variability (risky asset) could be an added value to the

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portfolio. In addition, Schmidt, *et al.* [24] contributed to the arguments for diversification of offshore wind asset since the spatial diversification incentivised by a premium feed-in tariff scheme. Further, deLlano-Paz, *et al.* [25] gave an exhaustive review of the literature concerning the application of MPT to the field of energy planning and electricity production, explaining the limits to the MPT and into the concept of risk, and adjustability to the reality of the electricity market alongside with its contribution from the financial and energy standpoint.

The present study aims to contribute to the state of the art by developing a risk-based approach to deal with the life-extension management of offshore wind assets. Markowitz's MPT obtains the optimal operational management strategy for targeted returns with minimal risk. To achieve this goal, firstly, a techno-economic life extension analysis is conducted to attain the mean value of return and variance from the mean value, which is denoted as risk. Afterwards, the resulting risk-return diagram is used to classify the offshore wind assets using unsupervised machine learning, k-means clustering algorithm. The appropriate weighting factor is estimated for a set of different offshore wind assets through an optimisation process that minimises the risk for a targeted mean of return. The study cases are generated for different stages of the life extension to give recommendations regarding how to navigate during a life extension with the efficient portfolios of offshore wind turbines.

2. Modern Portfolio Theory (MPT) and Portfolio Optimisation

Markowitz's MPT acknowledges the trade-off between the expected return and corresponding risk, and the theory argues that the expected return should be evaluated by an investor concerning the risk investor is willing to take to earn the expected return. Within this context, MPT helps to build multiple assets that maximise the expected returns for a given level of risk or minimise the risk for a given level of return.

The modern portfolio theory heavily relies on statistical time-series measures (moments). These statistical measures are mean value, standard deviation, covariance, cross-correlation, and auto-correlation. The mean value denotes the performance (arithmetic mean for expected, geometric mean for achieved performance), the standard deviation denotes the riskiness of the asset. The covariance indicates the systematic risk, which cannot be removed by diversifying the overall risk in the portfolio of assets). The cross-correlation denotes how two given assets move together, and the auto-correlation represents the informational efficiency of the asset that shows how it moves in time. The present study performs portfolio optimisation for life extension management based on the first four measures, assuming that the autocorrelation of all assets is zero, meaning that return on investment would reflect all the information without any time lag.

The correlation between the assets is as significant as the mean value and standard deviation because it defines to what extend the risk can be minimised within a diversified portfolio. As the correlation between the two assets gets -1, the total risk of the portfolio of those two assets becomes. Whereas when two assets are fully correlated, correlation equal to 1, the entire risk or standard deviation of the portfolio becomes the weighted sum of the standard deviations of those two assets.

The correlation effect on the success of the risk mitigation via diversification becomes more relevant for life extension of offshore wind turbines than the beginning of the life-cycle because the offshore wind assets are expected to be less correlated with each other over the service life.

Following the description given above, Markowitz's portfolio theory can be expressed as follows:

$$\mu_p = \sum_{i=1}^{N} w_i \mu_i \tag{1}$$

where μ_p is the mean value of returns of the portfolio and w_i is the weighting factor related to each asset, and μ_i is the mean value of returns of each asset. The variance of returns is expressed as follows:

$$\sigma_p^2 = \sum_{j=1}^{N}\left(w_j^2\sigma_j^2\right) + \sum_{j=1}^{N}\sum_{\substack{i=1\\i\neq j}}^{N}\left(w_j w_i \sigma_{ji}\right) \tag{2}$$

where σ_p is the standard deviation of return of the portfolio, which indicates the level of risk of the overall portfolio, σ_{ij} is the covariance between two assets, and it is calculated as:

$$\sigma_{ji} = \rho_{ji}\sigma_j\sigma_i \tag{3}$$

where ρ_{ij} is the correlation between the two assets. For a large number of assets, the standard deviation of return of the portfolio as follows:

$$\sigma_p^2 \cong \sum_{j=1}^{N}\sum_{\substack{i=1\\i\neq j}}^{N}\left(w_j w_i \sigma_{ji}\right) \tag{4}$$

As the correlation approximates 1, the portfolio's standard deviation approximates the weighted product of the standard deviation of return of each asset, which means that the portfolio selection does not reduce the risk caused by individual assets (idiosyncratic risk). Portfolio optimisation aims to minimise the idiosyncratic risk so that the portfolio possesses only the systematic risk that cannot be reduced by diversification.

In essence, the modern portfolio theory constitutes a multi-objective (maximum return, minimum risk) optimisation problem that leads to an efficient frontier. The efficient frontier is built similar to the Pareto optimality front (frontier), which accepts the riskier asset so long as the asset's mean value is higher or accepts a lower return so long as the asset is less risky. It is worth mentioning that the efficient frontier tends to be nonlinear, showing behaviours such as diminishing marginal return to risk. This means that it requires more risk-taking to get a unit increment of the expected return.

Another underlying assumption of the modern portfolio theory is that the asset return follows a normal distribution, which might not represent the reality as the distribution of the asset returns can be fat-tailed distribution and might have a tail and asymmetric dependence and can show non-stationary (time-varying) time series attributes. If failing to comply with these normality assumptions, the investor is subjected to the heavy downside risk, and a risk-averse investor is intolerant to the downside risk.

The critics of the modern portfolio theory suggest that there are significant flaws regarding the underlying assumptions, such as normality assumptions, returns reflecting complete information and risk definition assumption. To address these assumptions, post-modern portfolio theory was introduced, focusing on the downside risk of returns. The suspicious take on the modern portfolio theory and its place in the investment world has its merit; nevertheless, the application of the modern portfolio theory to the offshore wind asset managements is still quite an interesting research topic as the underlying assumptions regarding the return, volatility and correlation can be obtained through a number of statistical analyses and confirmed before the use of the MPT, which is essentially the case for the present work.

The line drawn from the risk-free asset r_f tangent to the efficient frontier is called the optimised risk/return relationship (Sharpe ratio) along the efficient frontier. The most efficient portfolio is identified as the highest Sharpe ratio. An investor who does not define a preference function (utility function), which is a function of risk-averseness, should accept the portfolio with the highest Sharpe ratio.

$$Sharpe\ Ratio = \frac{(\mu_p - r_f)}{\mu_p} \tag{5}$$

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The optimised portfolio with the highest Sharpe ratio is a concept that can be utilised for the diversified offshore wind asset portfolio. Nevertheless, it is also possible to attain efficient portfolios as a function of the risk-averseness of the decision-makers. One can be advised to accept more risk-tolerant preference at the beginning of the life extension. The level of risk-averseness could be increased towards the end of the life extension, and precisely the research question was undertaken in the present work.

3. Life Extension Assessment and Offshore Wind Asset Classification

The prerequisite of the modern portfolio selection is to have the first two moments of the sample offshore wind farm data, the mean value and standard deviation. The mean value denotes the expected return, and the standard deviation indicates the risk associated with the asset. To this end, a comprehensive life-cycle assessment covering both technical and economic aspects is conducted in a Monte Carlo simulation. The techno-economic life-cycle assessment results are used to classify different offshore wind assets based on a risk-return diagram.

The methodology used for the classification consists of 5 stages, as seen in **Figure 1**. The procedure commences with the preprocessing of data collected by the structural health monitoring system, followed by a corrosion-induced crack growth simulation and structural integrity analysis to estimate the maintenance interval and overall operational costs.

Figure 1. Flow chart for the development life extension classification

The appropriate risk premium for each offshore wind farm is defined to discount the free-cash-flow expected to attain during the life extension to reach an intrinsic value of an offshore wind farm life extension. The solutions are classified using the unsupervised machine learning technique, k-means clustering. The offshore wind farm projects are represented as asset classes with different expected return and risk class, which is the required input to apply modern portfolio theory providing recommendations for further risk or return expectations.

The monopile offshore wind turbines with a 5 MW power capacity are considered a reference ageing offshore wind structure because the monopile support structures are the most commonly used support structure type. A typical monopile OWT is illustrated in **Figure 2**, and Table 1 shows the characteristics of the monopile OWT.

Table 1 Characteristics of the monopile OWT [26-28]

Wind turbine	5 MW NREL

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Rated wind speed	11.8 m/s
The expected value of wind speed	9 m/s
Hub height (from the MSL)	86 m
Water depth (from the MSL)	40 m
Turbulence intensity	0.12
Integral length scale	340 m
Thrust coefficient (N/(m/s))	0.73
Structural & Aerodynamic damping	4% & 1%
Natural frequency	0.281 Hz
Diameter	6 m
Thickness	50 mm
Material constant	5.21E-13
Material exponent	3
Threshold stress intensity factor	2 MPa
Critical stress intensity factor	69 MPa.m$^{1/2}$
Yield stress	355 MPa
Plate breadth	0.1 m
Sigmoid Slope	0.2
Shift parameter	0.01

The techno-economic life extension assessment for offshore wind assets calculates the mean return based on the assumption that the offshore wind asset is appreciated based on the return on asset obtained annually. Because it is assumed that the offshore wind asset does not require any debt to fund its investment, it is reasonable to take that the risk premium is directly proportional to the variance from the mean value of returns, which can be derived by reversing the capital asset pricing formula to estimate the standard beta, in turn, the standard deviation.

The future earnings/cash flow of an offshore wind asset requires revenue and operational cost estimation. The revenue can be calculated by multiplying expected energy production by the feed-in tariff. The operating cost can be estimated using empirical formulas based on the operational intensity and wind turbine capacity. It is worth mentioning that the estimate made for future earnings rely heavily on the assumption and the success of empirical models used in the present study.

The present study considers the variables affecting the free cash flow within the scope of a semi-quantitative risk-based analysis, which was based on the likelihood of failing to obtain the predicted future earnings. These premiums are calibrated depending on the characteristics of the life-extension project and the economic environment under which the project is consented. The spread/corporate premium consists of equally weight premium components covering possible risk concerning obtaining expected free cash flow such as life extension project, project owner, microeconomics, macroeconomics, energy sector and financial market.

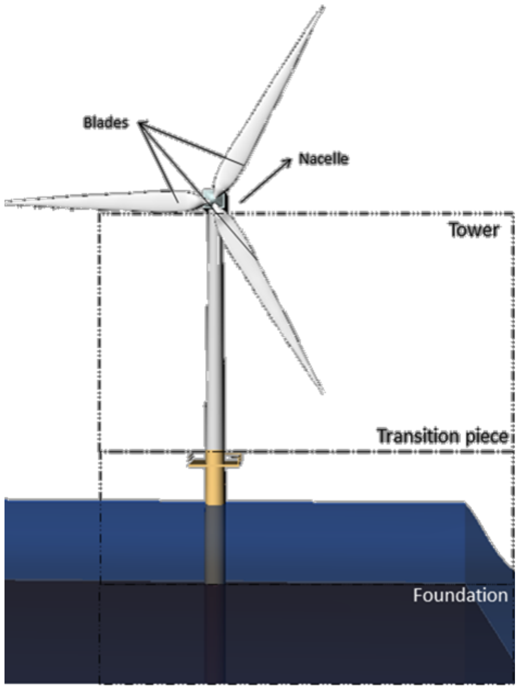

Figure 2. Typical monopile OWT structure

In the present study, the risk-free rate is assumed to be 1.5%, and the market return is 8.7%, and the volatility measure is 1.12. The variables considered in the free cash flow analysis and the extent to which these variables affect the interest rate are given in Table 2. The details of the techno-economic life extension assessment can be found in [29].

Table 2 Characteristic of variables involved in the intrinsic value analysis

Variables	E []	COV (%)	Distribution
Expected wind speed (m/s)	10	10	Weibull
Operation intensity	0.75	10	Normal
Wind farms size (unit)	30	20	Uniform
Life extension (year)	20	40	Uniform
Management efficiency	0.85	10	Normal
Availability & Capacity factor	0.95 & 0.44	10	Normal
Measured crack size (m)	0.010	20	Lognormal
Feed-in tariff (€/MWh)	120	20	Normal
Safety Class	5	50	Uniform

Figure 3 presents the results of the techno-economic analysis for different life extension projects over a risk (standard deviation of return on equity) –return (mean value of return on equity) diagram. The analysis is conducted for 200 life extension projects uniquely characterised based on the variables given in Table 2. The results show a pattern that complies with the expected high-risk high-return model to a certain point, and beyond that point, a higher risk cannot produce a higher return. This phenomenon is explained in economics as “the law of diminishing marginal returns”, which implies that after some certain level of capacity is reached, having an additional risk factor will indeed yield a minor change in return. On the other hand, being too risk-averse could cost the project not to produce any viable return. An efficient frontier is established for the life extension project to guide life extension management in light of these considerations.

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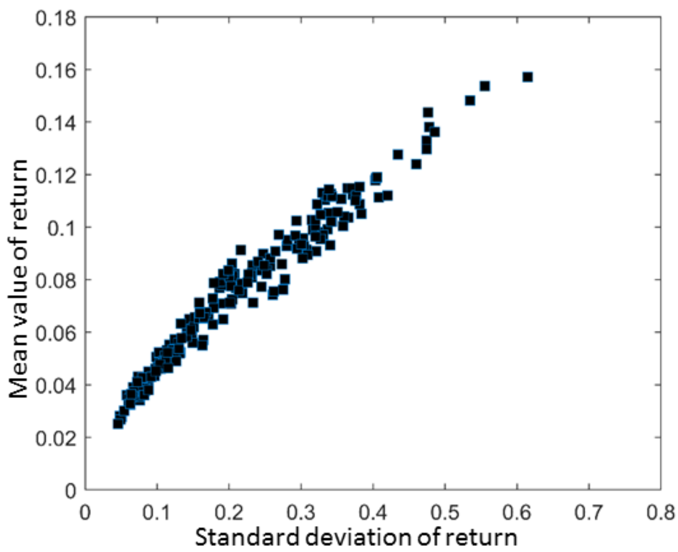
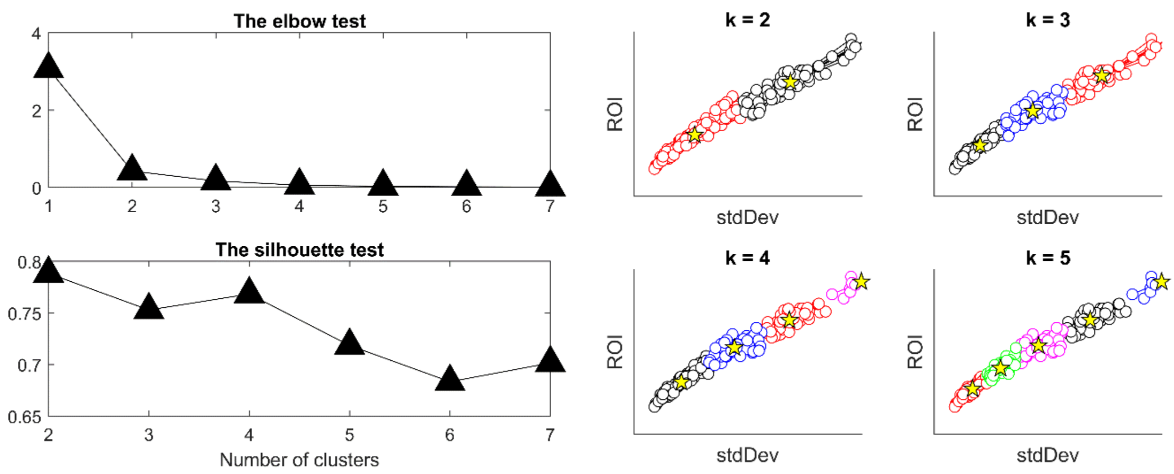


Figure 3. Risk-return diagram

The results of the techno-economic analysis are used to classify the offshore wind turbine. To this end, the k-means unsupervised machine learning (ML) algorithm is employed. Unlike supervised machine learning, the success rate of the k-means algorithm cannot be evaluated by training and testing error. Instead, the k-means ML algorithm employs quantitative and qualitative metrics to measure the performance of the ML algorithm. In this regard, the elbow test, silhouette test and visual inspection are used to measure the success of the classification concerning the number of clusters.

Figure 4 (**a**) shows quantitative test results in which the minimum elbow test score and the maximum silhouette score are targeted. At times when the quantitative tests result in multiple candidates, a visual test might be helpful. It can be argued that k = 2 or k = 4 are a reasonable choice for the number of clusters; however, the visual test indicates a classification with four groups would make a better choice (see **Figure 4** (**b**)).



(**a**) (**b**)

Figure 4. Quantitative (**a**) and qualitative test (**b**) for the k-means clustering

Figure 5 demonstrates the classified offshore wind assets on a risk-return diagram, where the mean value of return denotes return on investment, and the standard deviation indicates the risk. Four groups are identified as Group A, B, C and D. Asset class D is associated with the highest expected return and highest risk, whereas asset class A is associated with the lowest risk and lowest expected return.

A reasonable scenario would be starting in the region of high-risk and high return as Group D, and through risk mitigation strategies can be applied to make the overall offshore wind farm less risky asset group zones towards the end of the life extension.

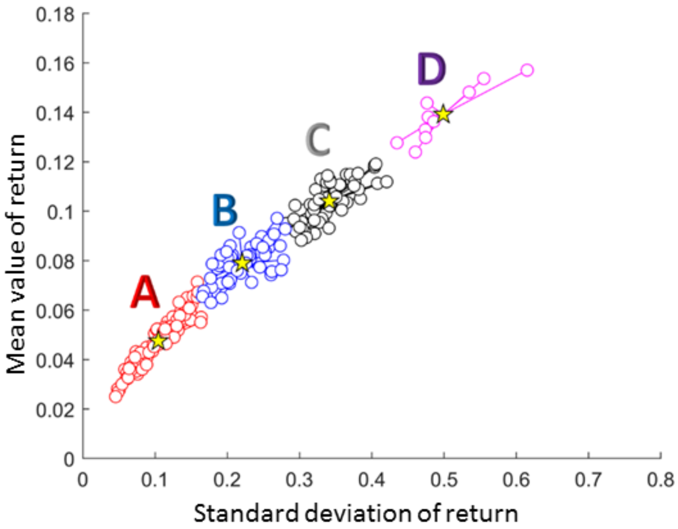
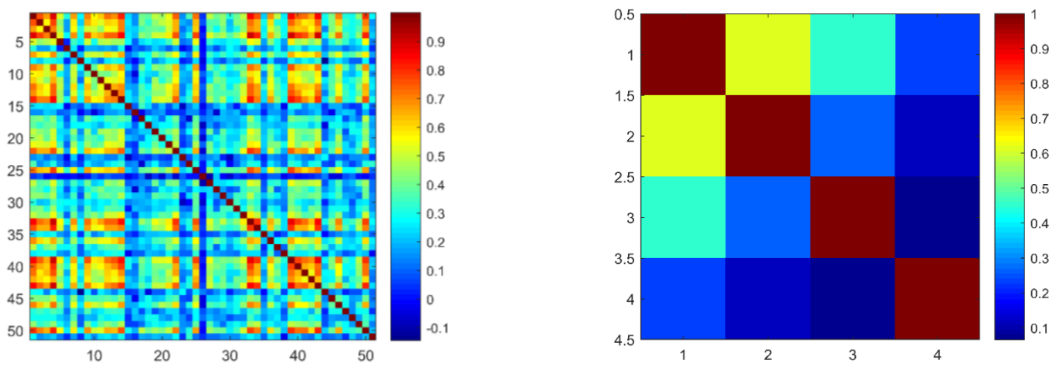


Figure 5. Classification of life extension projects in 4 groups

4. Case Studies and Discussion

The techno-economic analysis and k-means unsupervised ML algorithm result in the classified offshore wind assets on a risk-return diagram. The present section uses the provided data to conduct the mean-variance optimisation for offshore wind assets of different classes (classification). The modern portfolio theory requires the covariance matrix between the offshore wind assets besides the mean value and standard deviation. To this end, a time series of the mean value of returns is generated based on the monthly expected return and standard deviation of each offshore wind asset using sampling as white Gaussian noise. The generated time series are used to estimate the covariance and correlation matrix.

Although the techno-economic analysis resulted in 200 data points, for better visibility, the correlation matrix of 50 offshore wind asset is shown in Figure 6 (**a**). Figure 6 (**b**) demonstrates the correlation matrix of 4 offshore wind turbines deemed representative of four asset groups (A, B, C and D) as identified in the previous section.



(**a**) (**b**)

Figure 6. Correlation matrix for 50 simulated offshore wind asset (**a**) and 4 representative assets (**b**)

In the choice of the representative offshore wind turbines, it is aimed to have assets with different correlation, assuming that the offshore wind turbines might differ considerably from the wind turbine efficiency and structural condition standpoint after 25 years of service life.

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As far as the case studies are concerned, the life-extension is considered to have three phases. The first phase is the beginning of the life extension, where the investor can be more risk-tolerant and prefer the portfolio that would bring higher returns.

This phase can be investigated in two expected rates of return as 15% and 14%, as in **Figure 7** and **Figure 8**, respectively. The resulting portfolios must be along the efficient frontier. The results indicate that to achieve such expected returns, the offshore wind farms must have a significant portion of their offshore wind turbines operating conditions at asset class D (OWT_4).

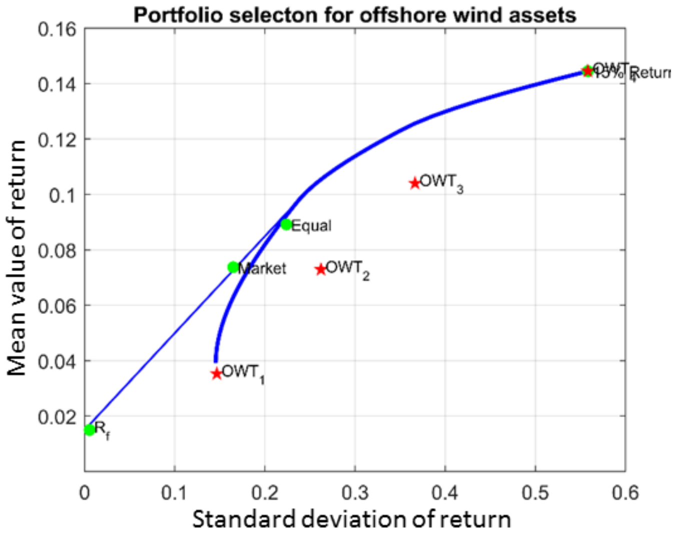

Figure 7. Mean value of returns as a function of standard deviation, 15% return and equal weights

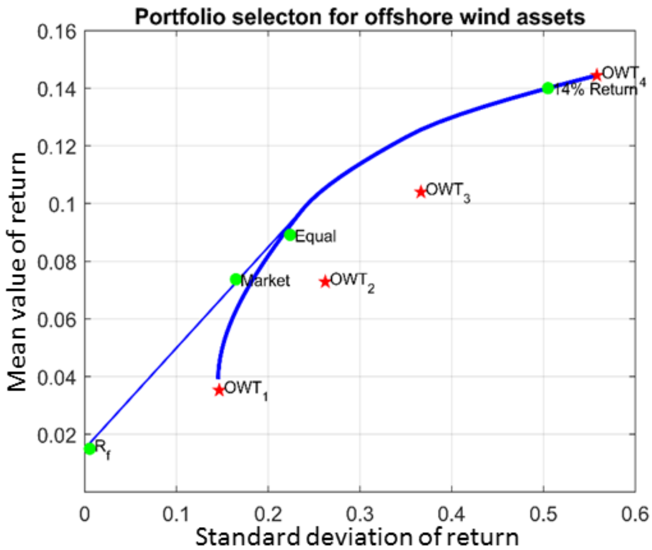

Figure 8. Mean value of returns as a function of standard deviation, 14% return and equal weights

As for the second phase, the offshore wind farm is considered to be halfway through the complete life extension. It is reasonable to argue that investors would prefer a less risky operation of the offshore wind farm as the structural conditions are worsening and the capacity factor of the offshore wind farm are decreased. The optimal portfolios on the efficient frontier are demonstrated for 12% and 10% mean value of the rate of return on investment (ROI) in **Figure 9** and **Figure 10**, respectively.

The results show that if the offshore wind turbines of different asset groups were equally weighted, the expected return rate would be lower than what the mean-variance optimisation suggested. For this phase, asset class B and C outweighs the other asset groups. Nevertheless, it is beneficial to have other asset groups with smaller portion to

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take advantage of the diversification effect on the risk mitigation. It should also be expected that as the correlation between the asset groups increases, the efficient portfolio curve gets closer to the assets, meaning that the overall portfolio risk becomes higher than the portfolio with less correlated asset groups.

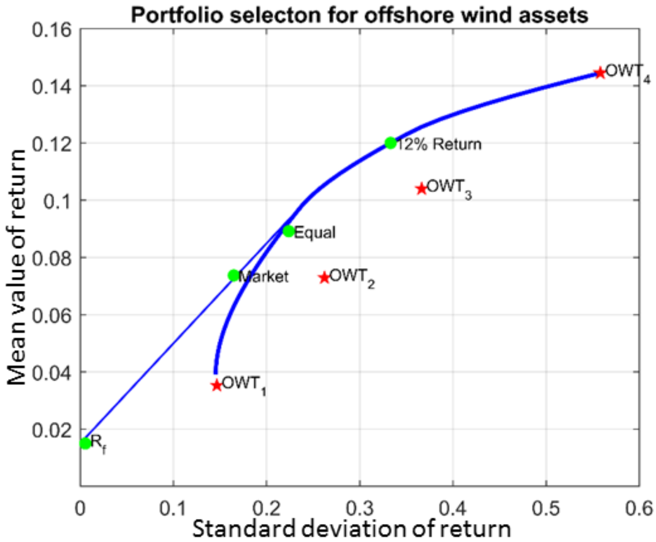

Figure 9. Mean value of ROI as a function of standard deviation, 12% return and equal weights

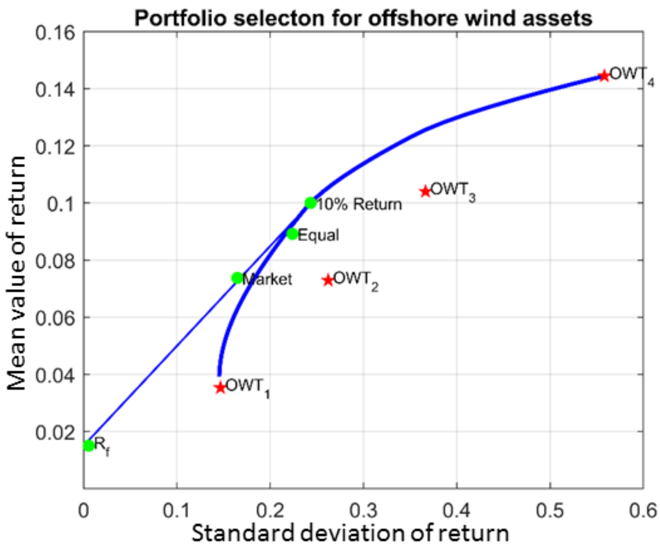

Figure 10. Mean value of ROI as a function of standard deviation, 10% return and equal weights

The investors' expectation would be different towards the end of the life extension. As a result of an intensive operation, the offshore wind assets should expect to have more structural integrity issue that needs to be attended by maintenance or even repair. A proactive management approach would be reducing the targeted rate of return, thus the risk.

Figure 11 shows the portfolio on the efficient frontier, which happens to be somewhere between an equally weighted portfolio and the market return in terms of return. **Figure 12** shows the portfolio selection that minimises the risk for the available asset groups. Although the low-risk asset class has the largest position in the optimal portfolio, the total risk of the offshore wind farm is less than the asset class A (OWT_1), which demonstrates the power of diversification on the offshore wind farm consisting of multiple offshore wind turbines with varying features.

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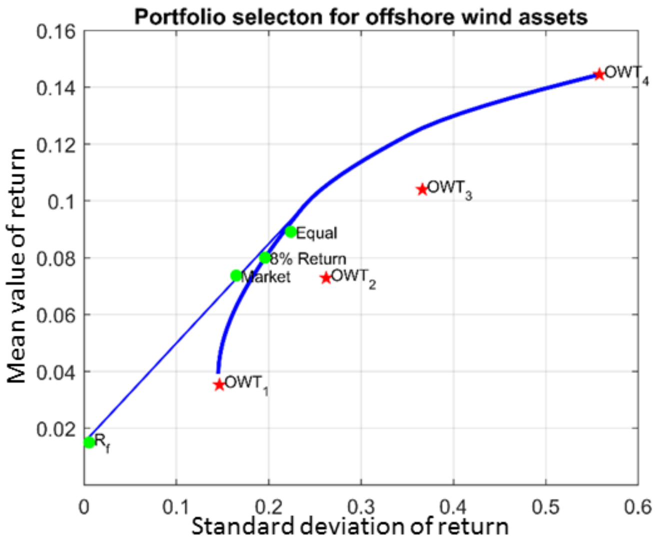

Figure 11. Mean value of ROI as a function of standard deviation, 8% return and equal weights

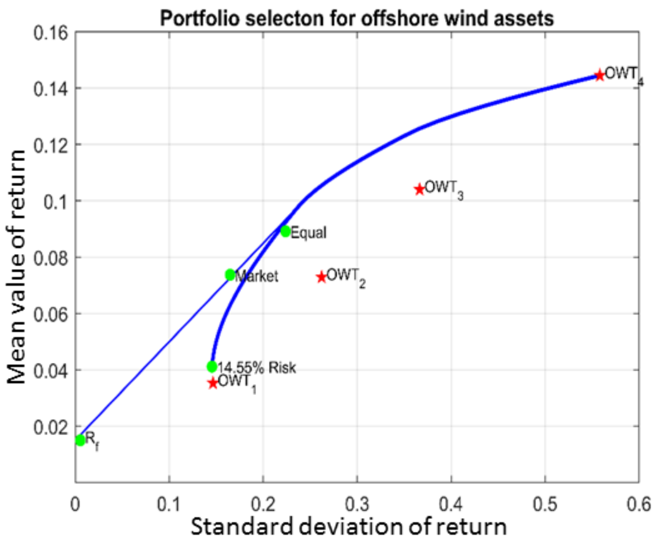

Figure 12. Mean value of ROI as a function of standard deviation, minimum risk (14.55%)

In addition to the portfolios optimised for the different phases of the life extension, decision-makers responsible for the life extension operational management might be interested in acquiring a portfolio of offshore wind assets that will maximise the how much excess return gained for having a risky asset, in other words, risk-adjusted return. The modern portfolio theory introduces this concept through the Sharpe [4] ratio.

Figure 13 shows the portfolio that maximises the Sharpe ratio and the portfolios generated for the portfolio at the market risk, the equally weighted portfolio, the portfolio targeting 12% return. The Sharpe ratio on the efficient frontier is also the point that intersects with a tangential line connecting to the risk-free asset type. This line is called the capital allocation line for investors who allocate the capital between the Sharpe ratio and risk-free assets in finance, which does not have any place in the present study.

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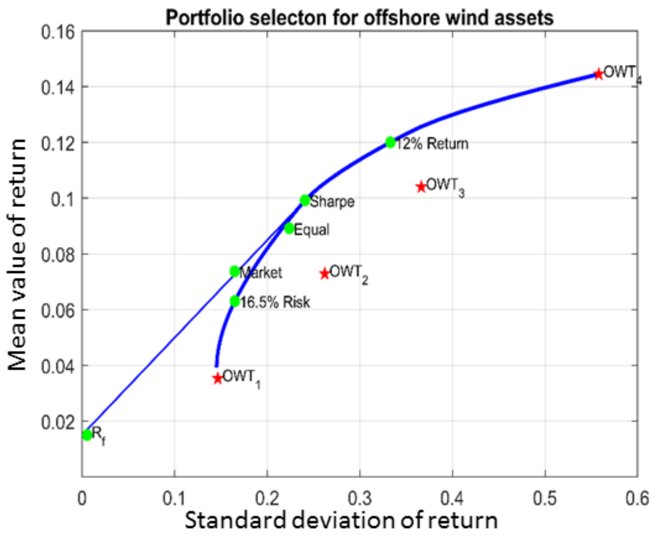

Figure 13. Optimal portfolio at the maximum Sharpe ratio

The Sharpe ratio is calculated based on the residual return (mean value of the rate of return – risk-free rate) divided by the standard deviation of the selected portfolio. This calculation is done for every portfolio on the efficient frontier and the portfolio that maximises the Sharpe ratio, therefore the most risk-adjusted return. The result of the optimisation maximises the Sharpe ratio is presented in **Figure 14**. The Sharp ratio decreases as the standard deviation of the return or the mean value of return increases because of the marginal diminishing return concept. The marginal diminishing return concept suggests that an investor needs to take higher risks to obtain excess return after the Sharpe ratio.

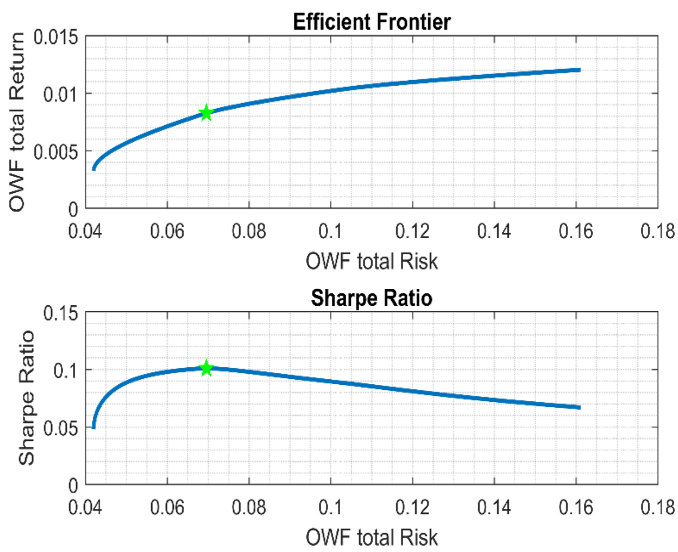

Figure 14. Sharpe ratio over different portfolios on efficient frontier

From the corporate finance point of view, the project's profitability measures the likes of the return on an asset, return on equity, return on investment (capital), return on sales, return on invested capital needs to be such a rate that compensates the appropriate hurdle rate that reflects the price for taking the risk to earn a given expected return. The generic investment concept is valid for financial, non-financial, corporate funding or project funding. The undeniable principle is to assess the added value (future earnings) brought to the investment (capital), accounting for the opportunity cost (weighted average cost of capital). Depending on the financial activities decided for the project, the performance measure can differ. However, ultimately the decision-makers seek projects/investments that will bring higher returns on the capital than the corresponding cost of capital.

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Within the scope of the present work, the analysis is conducted based on the assumptions that the offshore wind farms analysed for the life extension has got neither debt nor retained cash from the previous operating period. Based upon this assumption, the cost of capital associated with the offshore wind life extension is defined by the equity risk premium. The performance measure is considered a return on equity, even though equity, total asset, and initial capital would mean the same.

The equity risk premium is the price seen fit for taking the risk. Depending on the decision-makers view on the macroeconomics, microeconomics, long and short-term corporate strategy, energy market, and competitors inside and outside of the sector would determine the willingness to take the risk. The present study guides the decision-makers regarding the life extension of offshore wind farms. The asset type categorised as "high-risk high-return" is recommended for the beginning of the life extension; however, the decision-makers are urged to minimise the risk towards the end of the life extension to preserve its asset and avoid downside risk.

The present study analysed the riskiness of a life extension of an offshore wind farm via the perspective of two schools of thought. The first school of thought take the risk as the variance of return around an expected return, which is caused by the variability of the factors affecting the operating income of the offshore wind farm. The latter denotes the risk as any action taken other than having the well-diversified portfolio that maximises the Sharpe ratio. The last definition of risk assumes that the operators would minimise the risk of return by being well-diversified between the offshore wind assets, and the well-diversified portfolio of offshore wind turbines eliminate all the idiosyncratic risk associated with the individual asset and remain only with the systematic risk associated with the overall offshore wind farm and site. This means that for any chosen portfolio other than the well-diversified portfolio, there must be compensation.

The scope of the present study can be extended in the future by incorporating the capital asset pricing model, CAPM, within the modern portfolio theory to provide a relative measure of the risk premium for a different combination of asset groups accounting for macroeconomics, microeconomics, energy sectors strength, political and environmental sentiment. Such studies would allow for a more comprehensive look at the life-extension decisions related to operating, investing, and financing and help to have better judgements on the appropriate equity premium, the weighted average cost of capital, thus hurdle (discount) rate, which has utmost importance for project finance.

5. Conclusions

The present study developed a risk-based approach to find optimal life extension management strategies for offshore wind farms based on Markowitz's modern portfolio theory. The techno-economic life extension assessment was conducted considering the offshore wind turbines as cash-producing tangible assets; consequently, the mean value of return on investment and the deviation from the mean value were obtained to construct the risk-return diagram. K-means unsupervised machine learning algorithm classified four different asset groups for which the mean-variance optimisation was conducted. Finally, the case studies were generated considering different stages of the extended service life and the investors/decision-makers expectation.

The results of the mean-variance analysis indicated that a portfolio consisting of OWTs of different asset classes provides lower risk-taking for a required rate of return than an equally weighted portfolio. This conclusion is valid for all the case studies except for the required return of 15% and above. This conclusion supports the argument that the diversification between different offshore wind asset classes almost always helps with the risk mitigation during the life extension. However, the contribution of each asset groups to the overall portfolio changes with the required return, which varies depending on the life extension phase of the offshore wind farm is.

In addition to case studies created for different phases of life extension, the present study optimised a portfolio that maximises the ratio between the excess return gained for taking risk (Sharpe ratio). The portfolio with the maximum Sharpe ratio was estimated to be a 10% mean value of return on investment with a 24% standard deviation of return on investment. The decision-makers/investors must consider the portfolio return and risk and compare with the defined hurdle rate before accepting the terms of the life-extension project.

Furthermore, the outcome of this study enables creating a roadmap for sustainable and efficient life-cycle and extension management decisions by tuning the control parameters such as the operational intensity, the number of active offshore wind assets, risk hedging options, repowering, or decommissioning.

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