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Assessing the economical impact of innovations for offshore wind farms through a holistic modelling approach

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Abstract

In this work, a holistic modelling approach is developed and applied to the valuation of innovations in offshore wind energy. Two innovations are considered: 1) a more accurate modelling of vessel movement related to operations and maintenance activities and 2) an operational strategy for market participation. In both cases, a standard process was followed of first mapping the effects of the technologies on wind energy system's levels, then assessing them through development and augmentation of a holistic cost and valuation model. The process is demonstrated for each innovation and quantifies their potential impacts to LCoE and NPV respectively. The models and methods can be extended to other innovations for quantitative assessment of potential benefits.

1 Introduction

Offshore wind energy has seen numerous innovations in the past years that have both increased performance and reduced overall costs. For further competitiveness of offshore wind, it is necessary to continue identifying potential innovations and evaluating which ones are worth pursuing. By using a systems engineering approach with a holistic cost and valuation model, one can estimate the potential impact of such innovations.

Currently, there are several techno-economic assessment models available, both open source and commercially licensed (see for example, cost models including LEAN Wind [1], Romeo Wind [2], NREL ORBIT [3], ECN [4], among others). Techno-economic models can typically be classified as one of three categories: empirical, process or task-based, or schedule-based. Empirical models rely on past technology and past project's data as a reference in order to extrapolate costs and performance for new scenarios. Process, or task-based, models address the underlying activities associated with wind farm performance and cost (e.g. turbine installation) but do not address dynamics. Schedule-based models address the time-dependencies of activities and are the most detailed in terms of representing realistic system behavior. The trade-off of moving from empirical model to process-based model to schedule-based model is the computational expense versus the adaptability of the model to address system changes and innovations.

The key challenge in techno-economic assessment of innovations is to see the holistic picture of their impacts and represent them reliably in models that typically were designed without them in mind. As offshore wind continues to evolve, there is a need for a systematic approach to develop and adapt techno-economic and cost modelling frameworks for supporting assessment of new innovations.

This work aims to create a framework to evaluate the impact of innovations in the entire life cycle costs of an offshore wind farm project. This is done by: 1) Identifying the cost components of the wind farm life cycle impacted by the implementation of the innovative technology, 2) Developing a schedule-based, versatile cost model that has sufficient fidelity to accommodate various innovations, and then 3) Quantifying the effects of innovations in monetary terms and other economic metrics (either LCoE -levelized cost of energy- or NPV -net present value-). This new holistic approach takes the necessary inputs from various disciplines, such as wake modelling, reliability engineering, weather forecasting or electricity market, etc. to compute the economic metrics that demonstrate the economic impacts of the innovations. This methodology will be applied to an offshore wind farm in Belgium by using two innovations coming from PhairywinD project [5].

The first innovation investigates the use of computational fluid dynamics (CFD) modelling to compute the crew transfer vessel (CTV) movement relative to the monopiles [5]. Then, it uses this data to aid in the decision making process to conduct a maintenance operation, instead of using only wind speed and wave height as traditionally done; the goal being to increase the success rate of such operations.

The second innovation investigates the operational strategy of a wind farm to participate in both the day-ahead and ancillary markets. Traditionally, a wind farm will participate only in the day-ahead market. However, as the shares of renewable sources increase in the electricity grid, wind farms could also provide some reserved capacity for the grid which would increase their economic profit and increase the stability of the electricity grid.

2 Methodology

This holistic approach starts with mapping innovations to determine where the innovation affects the operational characteristics of the wind farm. Subsequently, the basic cost model is developed. The innovation is then integrated to the base cost model either by adding a new module or modifying the parameters of the base cost model. Since the cost model views the wind farm as part of an electricity generation system, it consists of all components necessary to convert wind speed data to the revenue from electricity market.

2.1 Mapping

The mapping is done through interviewing experts in that field of wind farm operations. For example, the author interviewed both Otary (wind farm owner and operator) and Siemens Gamesa (wind turbine manufacturer and service provider) in wind farm availability and CTV transfer issues to determine the risk assessment and method statement (RAMS). From the data gathered, modules and modifications have been proposed to integrate to the base cost model.

2.2 Base Cost Model

The base cost model used in this project consists of three main modules: the production module, the wind farm operations module and the electricity market module. The production module is used to calculate the potential wind farm production through wind data and wake model. The wind farm operation module computes the operating cost and turbines' availability with failure rates and maintenance costs. And lastly, the revenue of the farm is calculated in the electricity market module.

For the production module, Bastankhah's Gaussian wake model from DTU's PyWake tools [6] [7] has been implemented. By inputting the precise coordinates of the wind farm, the power production can be tabulated for each wind speed and wind direction specified [8]. This matrix is then looked up correspondingly with the time series wind data.

The wind farm operations module is implemented with inspiration from the NOWIcob model [9]; where a homogeneous Poisson's process (HPP) is used to randomize the wind turbine's components failure with component's specific failure rate and failure category [10] [11] [12]. For instance, a main bearing can have a small failure that requires two technicians in a CTV to remedy or it can have a catastrophic failure where a jack-up platform is needed to change the entire main bearing. The module runs through each hours of the wind farm lifetime, recording the state of wind turbines' availability and, in case of wind turbines' failures, recording the down time and the cost of these failures. The cost of failures data is obtained from Le et al [13]. In summary, the output of this module includes the turbines' availability and the costs associated to keep the turbines running.

The electricity market module is implemented as a two-price settlement electricity market in a European country. Currently, Belgium's market data is used [14], and wind farm behaves as a price taker. The module functions in the same way as a real electricity market where the wind farm operator must submit the forecast for the next day before the bidding gate closes. Then the revenue will be calculated based on the contracted quantity and the forecast errors. Furthermore, the electricity market module is able to accommodate any other innovation related to forecasting of atmospheric conditions as well. For the ancillary market, by definition, the revenue is calculated from the contracted quantity and the energy delivered. However, the price of a contracted quantity is almost always confidential. Therefore, the revenue from the ancillary market is calculated purely on the energy delivered to the market. [15] [16] [17]

2.3 Innovation 1: Improved Vessel Modelling

From the mapping and the base cost model, the first innovation can be integrated into the operational phase by estimating the success of the vessel transfer to the monopiles. The first direct impact is in the vessel operational cost: if the innovation improves the success, the model will show an improvement in OPEX. The secondary effect is in the turbine availability: if transferring the technicians has a better success rate, the turbine availability will increase. Then, the effect ultimately reduces the penalty pricing for production error in the day-ahead market. These impacts have been modelled in three steps.

In the first step, a matrix illustrating the waiting time for weather windows has been introduced. It is a table in which the probability of waiting time for a certain weather window can be looked up, where wind speed and wave height are within acceptable limits. For example, if 3 hours of maintenance are required, a weather window of 5 hours will be necessary - taking into account the travelling time. The waiting time table is then looked up, and the probability of waiting time for a 5-hour weather window is extracted. This probability is then used to randomize the outcome of the waiting time duration i.e. for a 5-hour window, the randomization process might result in a waiting time of 2 hours or 10 hours. The resulted waiting times matrix is calculated from historical metocean data from NREL ORBIT repository [18].

The second step is to calculate the success rate of the technicians transfer for two methods, the traditional method and the innovative method. For every mission duration, a decision vector is computed from sufficiently long enough forecasting time series data. For the traditional method, the decision to go is decided whether the wind and waves are within limits or not, while for the innovation method, the decision to go is decided whether the vessel movement is within acceleration limits or not.

In the second step, both traditional and innovation methods obviously requires the forecast data of wind speed, wind direction, wave height, wave period and wave direction data, and in addition, the results of CFD simulations based on such data. However, both the data and simulation results were not available at the time of the thesis writing, as it is yet to be done.[5]

To overcome the lack of CFD simulation results [5] and the lack of sufficient metocean data, the author instead conducted a sensitivity analysis of the success rate of the technicians transfer. Ultimately, any improvement in transfers' success, resulting from potentially any decision making method will be quantified through the improvement of the success rate. Hence, the sensitivity analysis served as a good proxy for innovation impact quantification. As a result, in the cost model, when a CTV operation is needed, the outcome of the transfer is randomized with respect to the success rate: if the transfer is not a success, then a second attempt is required; consequently extending the downtime of the turbine and implying the additional cost of chartering a second CTV. Therefore the economic impact of the sensitivity of the success rate is quantified.

In the third step, the base cost model's wind farm operation module has been augmented with the waiting time matrix and the success rate randomization. The Monte Carlo simulation is then used to calculate the average of the OPEX and availability of the wind farm. Therefore, whenever a turbine failure occurs, the waiting time and the success of the transfer is taken into account. And finally the economic metrics are calculated.

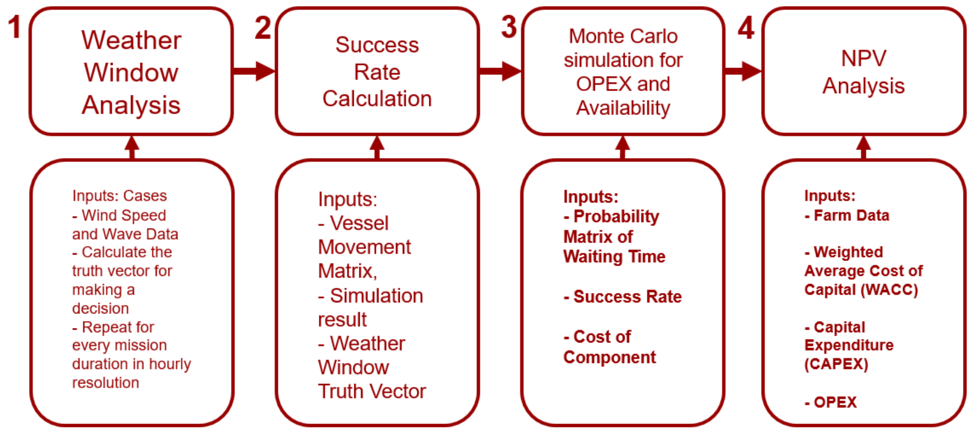

Figure 1: Concept of Innovation 1 implementation

2.4 Innovation 2: Market Operational Strategy

The second innovation deals with the wind farm operating strategies: when and how the wind farm should provide a secondary reserve to the grid. This reserved capacity is abbreviated as aFRR+ (automatic Frequency Restoration Reserve) in Belgium's market [15].

The wind farm's aFRR+ amount represents an amount of power that the wind farm holds back from the main electricity production, to sell in the reserve market instead of the day-ahead market.

For this innovation case, it is hypothesized that by providing the secondary reserve, the wind farm can receive an additional revenue stream from the electricity market. According to the interviews and mapping of the innovation, innovation two has been implemented in the electricity market module. In general, from the weather forecast, the wind farm will bid its electricity production in the day-ahead market and the aFRR+ capacity in the ancillary market. When the time comes, the wind farm must supply both the day-ahead and aFRR+ quantities. In this study, the wind farm will prioritize aFRR+ (as the wind farm is contractually bound to reserve this capacity). To assess this innovation, a full stream of electricity market operation from forecasting until revenue settlement is required which has been implemented in three steps.

In the first step, the cost model takes the forecast wind data and makes a bid for the electricity market by looking up the instantaneous power curve of the wind farm. In this work, the author has a time-series wind data, but does not have the forecast. Hence the forecast in this research is the "smoothed" version of the time-series using an exponential moving average technique, as suggested by P. Pinson [19]. The model then decides whether the farm has sufficient power to provide the fixed-amount aFRR+ quantity or not. In the case of low wind, the model will only bid in the day-ahead market. Then, the model will save the bid quantities (day-ahead and aFRR+) for the electricity market module. To prevent an aFRR+ bidding at a marginally low wind speed, a safety factor is introduced. Namely, it is used to govern the minimum amount of day-ahead quantity required to bid aFRR+, a safety factor of 1 means that the farm will only bid aFRR+, whereas a safety factor of 2 means that the wind farm has twice the amount of aFRR+ in the forecast and similarly for safety factor of 3.

In the second step, the model runs the wind farm operation module with 500 iterations. The model randomly selects N results to represent N turbines in the farm. With these turbines, the model then calculates the "actual" power production of the wind farm, taking into account the availability of these turbines. The production module allocates the production quantity to aFRR+ first, and the day-ahead quantity afterwards. Therefore, the wind farm will fulfill its contractual obligation to provide a reserved capacity to the grid and it will take the revenue lost from the deviation of its production normally assigned for the day-ahead market.

In the third step, the model passes the bid quantity, the production quantity and associated prices data to the electricity market module. The revenue calculated depends on, firstly, how accurate the forecast is (deviation between bid and actual supply); secondly, how many turbines are operational (compounding the deviation further); and thirdly, what the market regulation states are (whether the wind farm deviation helps the grid state or not). The forecast accuracy impacts directly the revenue stream as it always benefits more to be accurate [19] [20]. The availability of the turbines is also imperative, as its effect will cumulate with the deviation already originated from the forecast inaccuracy. At the bidding stage, the model assumes that all turbines will be operational and the farm will bid at its full capacity. Additionally, the market regulation state may or may not help the wind farm. Namely, if the deviation actually helps returning the grid to the balance state, then the deviating quantity will get a fair market price. On the contrary, if the deviation throws the system further away from the stability, the wind farm will receive a punitive price [17].

At the end of these implementations, the economic metrics can be calculated. NPV is used for assessments as LCoE does not take the revenue into account.

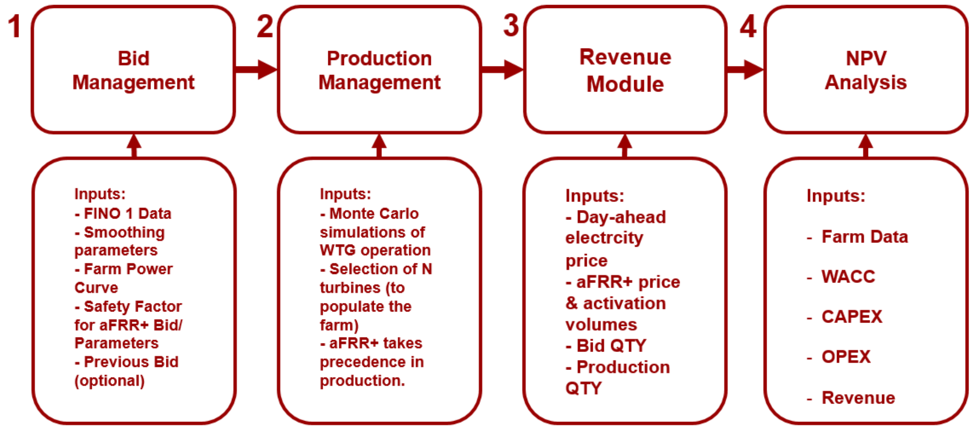

Figure 2: Concept of Innovation 2 implementation

2.5 Assumptions and Limitations

Although the cost model and the approach presented here are versatile and can take several data inputs such as failure rate, components' costs, they still have limitations mainly related with the input data accuracy which can be listed as following:

- The failure rates data used in this study contain data from several types of wind turbines, from several manufacturers, from several hub heights and several locations. Therefore, they cannot represent the actual failure rates of the wind turbines used in this study.
- It is assumed that the components have a constant failure rate and will function at 100% performance until failure. There will be neither curtailment to prolong the component life nor condition monitoring for preventive maintenance.
- The cost model does not sufficiently address the construction part of the wind farm, as it mainly deals with the operational part.
- The cost model is independent of the type of offshore wind farm foundation types. It is because floating offshore wind farms still use the CTV to conduct minor maintenance; the only modifications necessary are the failures that require the towing of WTG back to the mobilization port - by adjusting the cost of failures and the down time associated to the new process.
- In the OPEX module, once the waiting time period is over, the CTV sailing will be executed. By using the randomization of the waiting time matrix, the model has already taken into account the weather uncertainty. As a result, no weather forecast was utilized to dynamically plan the CTV sailing.

With similar practices to other cost models, the robustness of the results comes from the use of Monte Carlo simulations to average out any extreme values from the Gaussian random variable used in the wind farm operational modelling. The OPEX, LCoE and NPV are derived from the mean of the Monte Carlo simulations results and therefore the uncertainty available is the statistical uncertainty.

2.6 Case Study set up: Mermaid Wind Farm

In this study, since PhairywinD project is based in Belgium, Mermaid wind farm has been chosen. The wind farm is located in the Belgium North sea and recently went into operation phase. It boasts 28 Siemens Gamesa SG8.6-167 turbines [8]. Since the power curve of this wind turbine is confidential, the power curve from LEANWind 8MW Turbine [21] is used. Furthermore, the wind speed and wind directions are obtained from FINO1 meteorological mast in the German North sea [22] since the local wind measurements of Mermaid wind farm are not publicly available. From the wind turbine coordinates and the power curve, both AEP and instantaneous power production are calculated while taking the wake of the turbines into account, figure 3. The data is then passed to the operational module to compute the availability and OPEX. The wind farm power curve is then shown in figure 4. It can be clearly seen from the power curve when the wind farm has one, two or three turbines down. This means that the availability model functions as expected.

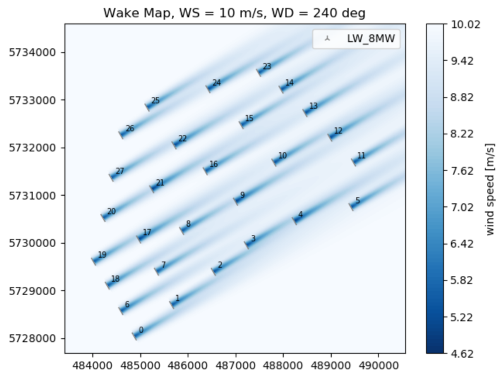

Figure 3: Mermaid Wake Map

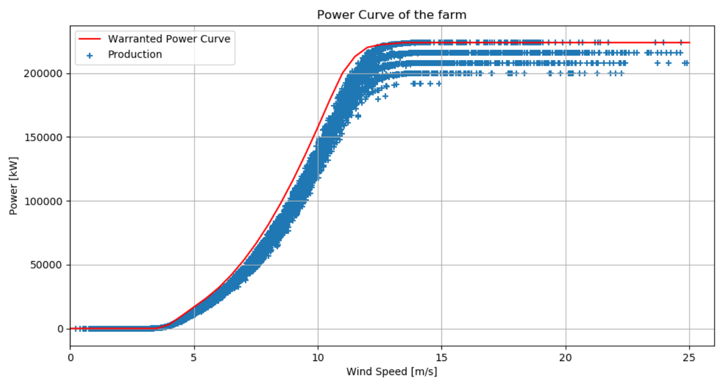

Figure 4: Mermaid's power curve, with turbine(s) failures

For innovation 1, the case has been set up to vary the success rate of the technicians transfer, and the electricity market module uses the Power Purchasing Agreement (PPA) price published by Otary (owner of Mermaid wind farm) at 79 EUR/MWh. A CTV charter rate is at 5000 EUR per day, according to the interview with Otary. A Monte Carlo simulation has been utilized at 4000 iterations per case.

For innovation 2, the case has been set up as a full factor analysis between the aFRR+ quantity and the safety factor. The aFRR+ quantity varies from 0 to 15 MW and safety factor varies from 1 to 3. A Monte Carlo simulation has been utilized at 500 iterations per case. To eliminate any influence of turbines' availability, a "perfect farm" has been implemented by setting the availability to 100% at all times. This "perfect farm" removes any deviation due to wind turbines failures. Furthermore, to remove the effect of forecast errors in the cost model, real wind time-series data has been used as a bid, to create a "perfect foresight" situation. Lastly, a case with a perfect farm and a perfect foresight combined has been conducted to demonstrate whether the innovation does indeed have the same effect in both real and ideal situations.

Cases	WTG Availability	Foresight	aFRR+ [MW]	Safety Factor
Normal	Normal	Normal	0,5,10,15	1,2,3
Perfect Farm	Perfect	Normal	0,5,10,15	1,2,3
Perfect Foresight	Normal	Perfect	0,5,10,15	1,2,3
All Perfect	Perfect	Perfect	0,5,10,15	1,2,3

Table 1: Innovation 2 cases set up

3 Results

For the first innovation, the Monte Carlo analysis shows that this innovation has little to insignificant impact on the reduction of OPEX per turbine and subsequently the same effect is seen for LCoE (between 115.4 and 116.75 EUR/MWh). The main gain is in the wind turbines' availability as it has increased from 95.5% to 96% when comparing the success rate of 60% to 100%: figure 5. The reasons for these marginal values are due to the vessel charter rates and the cost of the failures. A CTV is significantly cheaper to rent and operate, compared to a jack-up vessel; and the failures that require a CTV are substantially cheaper than the failures that require a jack-up vessel. Therefore, any improvement in cost will be eclipsed by a larger, more expensive failure that requires a jack-up vessel. In addition to these, it can be seen in this box plot figure 6, that the means of annual OPEX is relatively constant throughout all the success rates range, whereas the outlier lies above 2 mEUR as a result of more expensive failures. From the electricity market module, the improvement on one year's revenue is estimated at 68,430 EUR per year. Should one extrapolate this over lifetime, this first innovation has a potential to save 1.71 mEUR.

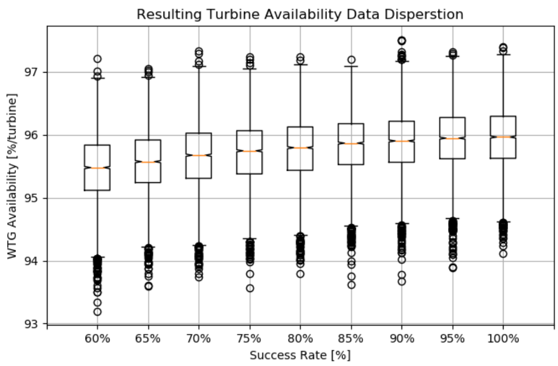

Figure 5: Resulting availability, with success rate from 60% to 100%

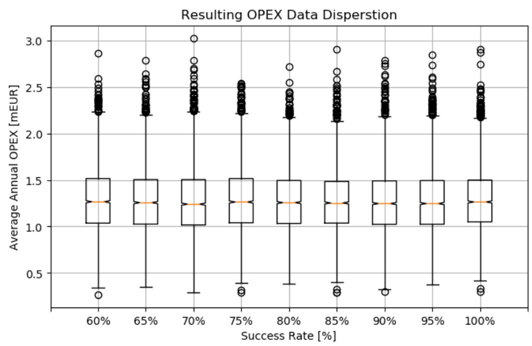

Figure 6: OPEX from innovation 1

For the second innovation, the cost model shows that by providing an aFRR+ capacity, the wind farm revenue improves. The improvement is on the condition that the aFRR+ quantity is not too large. From figure 7, the revenue of a wind farm that offers aFRR+ at a safety factor of 2 or even 3 has a better revenue compared to not offering some. This result is further reinforced by using imaginary wind farms with perfect availability and with perfect foresight, as seen in figure 8. From figure 8, the total revenue is higher compared to the normal case because now the wind farm has all turbines available at all times and makes no mistake in the bidding stage, as evidenced by a smooth curve. However, these results are subjected to the market data used and various assumptions entailed in the set up of case studies. From table 2, the NPV is negative because the wind farm was built with the PPA price in its financial assumption, whereas, in the case of this study, it is subjected to the free market prices as the PPA price guarantees a much higher revenue compared to the free market revenue. As a result from NPV values, offering aFRR+ results in a better financial position for the wind farm.

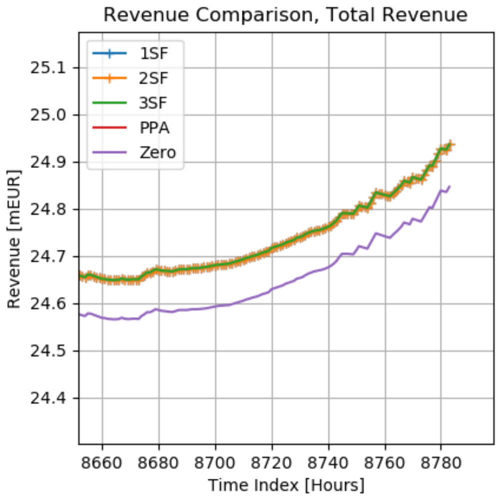

Figure 7: Revenues streams from offering 5MW of aFRR+, normal case

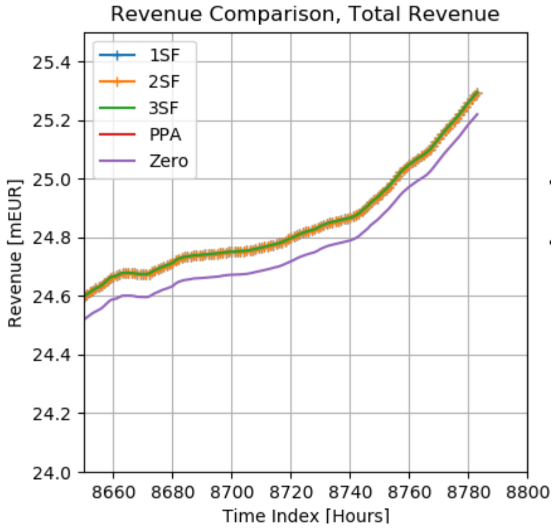

Figure 8: Revenue streams from offering 5MW aFRR+, perfect farm & foresight

Cases	Day Ahead	Balancing	aFRR+	Total [mEUR]	NPV [mEUR]
0 MW, Base Case	28.29	-3.603	0.00	24.69	-839.75
5 MW, Normal, SF1	27.18	-3.545	1.13	24.78	-838.31
5 MW, Both Perfect, SF1	24.15	0.00	1.13	25.29	-832.56

Table 2: Selected results from offering 5MW aFRR+ cases

4 Conclusions

This methodology shows that mapping innovations to an appropriate stage of a wind farm, coupled with a cost model that views the wind farm as a system, is successful in quantifying the economic impact of innovations. Furthermore, because of the modularity and holistic nature of the systems engineering approach, a broad range of innovations can be modelled through modifications to the framework. The resulting framework and methodology can thus support ongoing evaluation of offshore wind innovations to improve future wind farms profitability and competitiveness.

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