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Profitability of hybrid power plants in European markets

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Abstract. As markets continue to evolve, hybrid power plants (HPPs) are attracting the interest of plant operators and industry players alike. With their ability to provide flexible dispatchability, HPPs are poised to become a competitive solution in future energy markets, particularly in grid ancillary markets (such as frequency control, reactive power control and black-start). Moreover, resource complementarities present in some sites have the potential to significantly improve production predictability of collocated HPPs.To assess the profitability of HPPs in European markets, a hybrid sizing algorithm is applied to three locations across Europe with distinct resource distribution characteristics. The sizing tool implemented includes several novel features that are not typically incorporated into existing sizing software currently available on the market. This includes turbine selection, a simplified physical design of the wind power plant, a surrogate wake model, and a simplified solar panel degradation model. NPV-over-CAPEX optimal plant designs, tend to favor hybridization, by either collocating wind and solar power with storage, or only solar power with storage. On the hand, minimizing the levelized cost of energy generally results in single-technology power plants. The results show significant potential for hybrid power plants in European markets. However, to truly demonstrate their economic competitiveness, the focus should shift from LCOE to other optimization metrics that consider revenue from different electricity markets.

1. Introduction

There is an increasing interest in hybrid power plants (HPP) combining solar and battery, wind and battery, or a combination of all three. This trend is due to the continuously decreasing prices of Lithium-ion batteries and renewable energy technology. By the year 2020, 7 hybrid wind/solar power plants and 22 wind farms co-located with storage were in operation in Europe [1].

An increasing share of renewables integrated into the power grid has led to electricity markets shifting focus from mean energy production to value of energy delivered [2]. To adapt to this paradigm shift, design objectives which initially focused on minimization of levelized cost of energy should now consider net profit maximization from time varying revenue streams [3]. HPPs are increasingly being considered by energy providers, due to their ability to offer flexible dispatchability and ancillary services to the grid. In terms of reliability and flexibility, HPPs are more similar to traditional power plants than single renewable technology power plants.

Hybridization benefits also include economies of scope through shared grid connections, reduced land costs, and streamlined project planning resources. The joint probability distribution of the renewable energy resources may also be a driving factor, as it could enhance predictability and controllability of the supply from the plant.

The design considerations of the stand-alone wind and solar plant apply to the hybrid plant, in addition to those imposed by their colocation [4]. When designing an HPP, there is often a trade-off between designing multiple aspects as a whole and designing each individual technology within its field. On the one hand, optimizing the design of each technology independently, allows for more efficient systems within their specific domain. On the other, designing multiple aspects with a broader view leads to a more integrated and efficient system design.

The sizing and optimization of hybrid power plants are critical tasks for ensuring cost-effective and sustainable energy production. Fortunately, there are many commercial and open-source software tools available to support these tasks. Hybrid Optimization and Performance Platform (HOPP) is a design software for optimizing co-located, utility-scale hybrid plants comprising of wind, solar, battery, and Power-to-X [5]. The software provides optimal sizing, down to the component level. It takes into account physical design constraints, such as shadow flicker effects and irregular boundaries, when optimizing the layout of wind and solar power plants.

HOMER Pro is a micro-grid software, developed by HOMER Energy, to efficiently optimize micro-grid designs [6]. It simulates the optimal operation of the system by making energy balance calculations. Its main feature is providing the feasible system configuration with the least net present cost. Additionally, the software offers a sensitivity analysis that repeats the optimization process for each specified sensitivity variable.

GE's FLEXIQ is a modeling tool that evaluates the economics of hybrid renewable power plant projects and optimizes system configurations to maximize value. The tool provides optimal hybrid architecture and detailed optimal operation, optimizing plant configuration and providing a techno-economic evaluation. It also includes a power system management (PMS) and energy system management (EMS), allowing for active and reactive power control through the plant controller. The EMS enhances asset dispatch schedules to maximize profits, allowing for efficient and effective management of hybrid power plants [7].

This paper focuses on the sizing of utility-scale wind and solar hybrid plants coupled with battery, comparing the results of cost-based designs to value-based designs. While the utility sector has traditionally been driven by the LCOE metric, value-based metrics may offer a more comprehensive viewpoint [8] [9] [10].

2. Method

HyDesign is a state-of-the-art optimization tool that provides the optimal hybrid plant sizing based on a user specified financial metric [11], such as net present value over capital costs (NPV/CAPEX) or levelized cost of energy (LCOE). The associated workflow is shown in Figure 1. The design variables of the optimization include wind turbine design (blade tip to ground clearance, specific power, rated power), wind plant design (number of wind turbines, wind power density), solar plant design (AC power, surface tilt angle, surface azimuth angle, DC/AC ratio), battery sizing (power rating, energy storage duration).

The optimization engine sends design variables to wind power plant (WPP) and photovoltaic plant (PVP) and energy management system (EMS) model. The WPP and PVP models are informed by user-specified weather conditions. Based on this information, operational timeseries are estimated, and used to inform a finance model, which returns a quantity of interest to the optimization engine.

The sizing problem is implemented in OpenMDAO. It is an open-source optimization framework for efficient multidisciplinary optimization [12]. It is ideal for a sizing optimization due to its modular structure, which allows for independent modelling of components with different disciplines, and effectively handling their integration in the entire model.

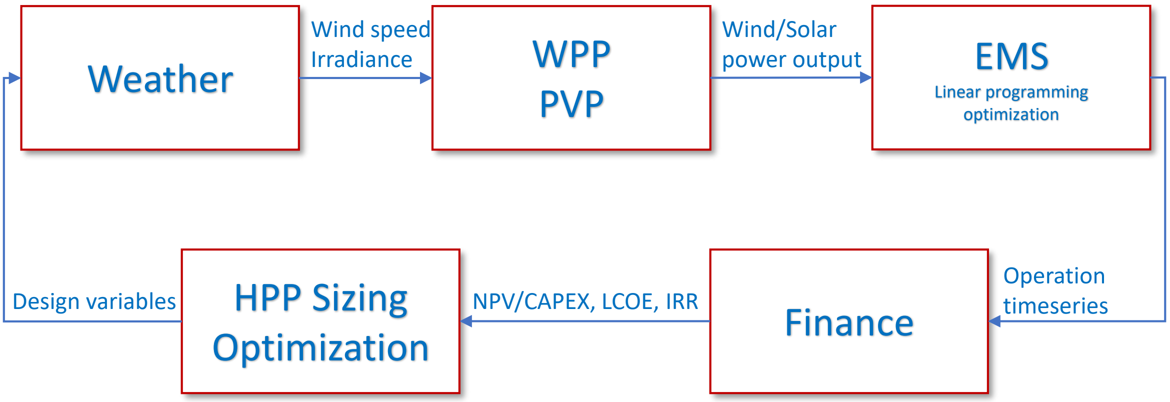

Figure 1. High level workflow of HyDesign

2.1. Weather

The wind and solar resources are modelled in detail using the ERA5 and ERA5-land reanalysis datasets [13]. The mean wind speed from Global Wind Atlas 3 (GWA3) [14] is then used to augment the precision of the wind speed data, by considering the effects of the terrain.

To speed up the optimization, a user specified number of weeks per season are selected. The selected weather data is then transformed to match the same probabilistic distribution as the entire weather dataset.

2.2. Wind and PV power plant models

To simulate the wind power production, a surrogate model was built using DTU's database of wind turbines. It generates the power and thrust curves of the turbine given its specific power. A surrogate model was also developed to estimate the wake losses as a function of the installation density, number of turbines and specific power of the turbine. The output of the surrogate model is a rectified power curve that takes into consideration the wake effect, providing a more realistic representation of the power output from the wind turbines in the plant.

PV production is modelled using a generic 1MW PV plant configuration. To account for PV panel degradation, a linear interpolation is applied to estimate the decrease in capacity throughout the panel lifespan, based on a yearly degradation rate.

2.3. Energy management system

The sizing problem includes an energy management system (EMS) optimization, based on CPLEX (MILP optimization). The optimization is deterministic and assumes perfect forecasting of weather conditions. The EMS determines when to charge or discharge the battery with the aim of maximizing the revenues and minimizing penalty costs during peak hours when applicable. The model accepts the wind and solar power generation timeseries as input, and returns the optimal battery operation, to be considered in the financial evaluations. Figure 2 demonstrates how the EMS charges the battery during periods of low electricity price and discharges the battery during periods of high electricity price.

2.4. Financial evaluation

A simple PV plant cost model estimates the total capital expenditure costs and operational and maintenance costs as a function of installed capacity and cost per MW of PV installed.

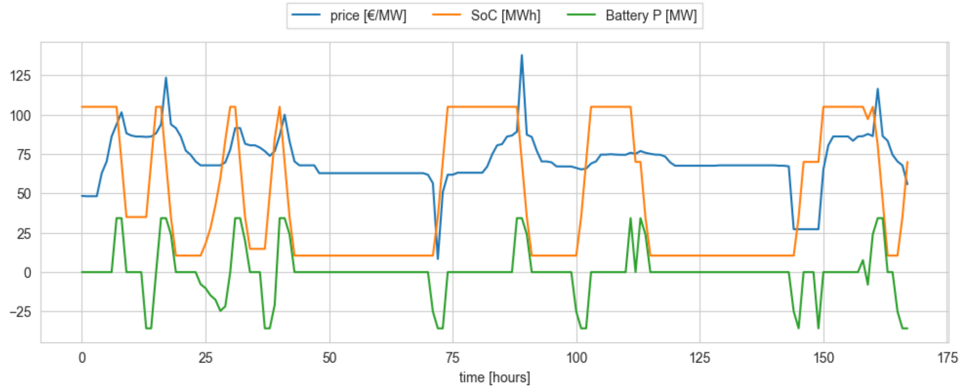

Figure 2. Electricity price and battery state of charge and power timeseries over a one-week period

WISDEM's cost and scaling model, developed in NREL [15], is used to evaluate the cost of the wind power plant. The model provides as output a cost scaling factor by specifying the unit costs and technical specifications of a reference wind turbine.

Battery costs are estimated using a simple battery cost model. The model calculates the total capital expenditure costs and operational and maintenance costs as a function of the battery energy and power capacity.

Costs of grid connection, balance of system, and land are also considered.

In the financial evaluation of the model, the net present value (NPV) and levelized cost of energy (LCOE) are calculated as followed:

$$LCOE = \frac{C_L}{AEP_L} \tag{1}$$

and

$$NPV = \sum_{\forall y} \frac{R_y}{(1 + WACC_{tx})^y} \tag{2}$$

where R_y is defined as:

$$R_y = \begin{cases} -C_H \text{ for } y = 0 \\ \overline{i_y} \text{ for } y > 0 \end{cases} \tag{3}$$

$\overline{i_y}$ is the average revenue over the year and is defined as:

$$\overline{i_y} = \left(\langle pr(t)H(t) - l\rangle_y - O_H\right)(1 - r_{tax})(1 - \text{ WACC}_{tx}) \tag{4}$$

C_L is defined as:

$$C_L = \sum_{\forall y} \frac{O_H}{(1 + c)^y} \tag{5}$$

The $WACC_{tx}$ stands for the weighted average cost of capital after tax:

$$WACC_{tx} = \frac{C_W \text{ WACC }_W + C_S \text{ WACC }_S + C_b \text{ WACC }_b + C_{sh} \text{ WACC }_{sh}}{C_H} \tag{6}$$

$WACC_{sh}$ stands for shared costs weighted average cost of capital :

$$\text{WACC}_{sh} = \frac{\text{WACC}_{W} + \text{WACC}_{S} + \text{WACC}_{b}}{3} \tag{7}$$

Where $WACC_W$, $WACC_S$, $WACC_B$, $WACC_{sh}$ are the weighted average cost of wind, solar, battery and shared electrical costs. Total capital costs and operational costs are defined as followed:

$$C_H = C_W + C_S + C_b + C_{sh} \tag{8}$$

$$O_H = O_W + O_S + O_b + O_{sh} \tag{9}$$

where: C_W, C_S, C_B, C_{sh} stand for CAPEX of wind, solar, battery and shared technology costs respectively. O_W, O_S, O_B, O_{sh} stand for OPEX of wind, solar, battery and shared technology costs respectively

2.5. Optimization

Surrogate based optimization is used to solve the sizing problem, using a modified parallel efficient global optimization algorithm [16]. Surrogate based optimization relies on building a surrogate (Gaussian process) as a function of all design variables. The algorithm is an iterative method that proposes new model simulations that balance exploration of the design space and exploitation of the trends discovered.

3. Case study

The hybrid sizing algorithm is applied to three locations in Europe: a site with high wind resources in Denmark (Lat: 55.23°, Long: 11.94°), a second site with high solar resources in France (Lat: 44.42°, Long: 4.22°), and a third site with average wind and solar resources situated in Germany (Lat: 49.31°, Long: 10.76°). The selection of these sites was based on the Global Wind Atlas [17] and Global Solar Atlas [18] maps, where darker colors indicate higher wind and solar resources, respectively.

Using the Balmorel model, electricity price data is predicted for the year 2030. Balmorel is a bottom-up partial equilibrium energy system optimisation model with a special focus on electricity and district heating sectors [19]. It can be used to forecast electricity prices across various regions in Europe for future years, typically up to 20 years in advance.

The price predictions generated using Balmorel were based on 2012 weather data assumptions. To maintain consistency, 25 years' worth of weather data was generated using the same dataset. 25 years corresponds to the projected lifetime of the power plant.

Figures 3, 4, and 5 display the hourly median and quantiles per season of unit wind and solar generation, as well as electricity price in the regions where the sites are situated. The figures illustrate the 5th, 15th, 25th, 35th, 50th (median), 65th, 75th, 85th, and 95th quantiles, with colours fading from the median. The plots provide insights into the seasonal variations of renewable energy generation and electricity prices in the different regions. The hourly median of electricity prices across all three locations and all seasons exhibits a consistent trend, with prices peaking generally between 4 PM and 8 PM. The data suggests that electricity prices are highest during the late afternoon and early evening hours, when there is typically higher demand for electricity due to people returning home and using more appliances for cooking, lighting, and heating/cooling.

Figure 3 highlights the first site's potential for high wind power output all year around. Wind power production levels are consistently high during the winter, spring, and fall seasons with a noticeable drop in wind production during the summer season.

The power production from wind resources in the chosen sunny site in France appears to be relatively low across all seasons, see Figure 4. However, the site boasts abundant solar resources

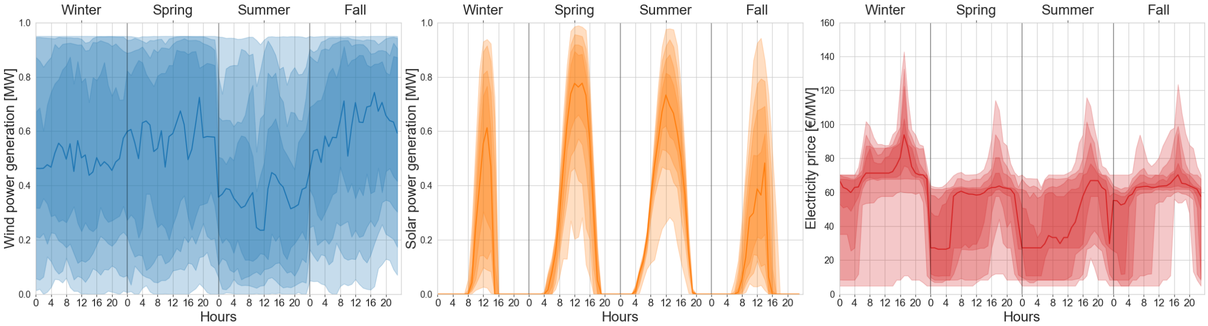

Figure 3. Hourly median and quantiles per season of a 1 MW wind turbine power generation (left), 1 MW installed PV power generation (middle), and electricity price (right) **in the good wind site situated in Denmark.** Wind power generation considers the following WPP specifications: clearance = 49, specific power = 321, rated power = 5, wind power density = 7. Solar plant generation considers the following panel specifications: tilt angle = 46, azimuth angle= 210. Darker colours represent higher probability.

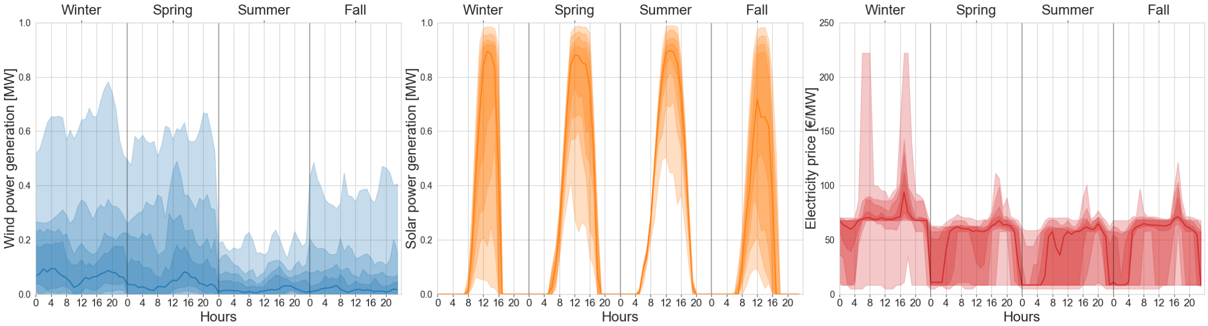

Figure 4. Hourly median and quantiles per season of a 1 MW wind turbine power generation (left), 1 MW installed PV power generation (middle), and electricity price (right) **in the good solar site situated in France.** Wind power generation considers the following WPP specifications: clearance = 49, specific power = 321, rated power = 5, wind power density = 7. Solar plant generation considers the following panel specifications: tilt angle = 44, azimuth angle= 210. Darker colours represent higher probability.

throughout the year, with peak production occurring during the summer when sunlight hours are longer compared to other seasons. Solar energy production dominates during the daytime hours, while wind energy production is consistently low throughout the day and night.

Figure 5 shows that the third site, located in Germany, has average wind resources that peak during the winter season. The solar production at this site is also relatively good, although lower than that of the second site. The plots show a complementary relationship between wind and solar resources at this site. Solar production peaks in the middle of the day when wind resources are low, and wind resources pick up again in the early evening when solar production begins to decline.

The wind and solar technology costs are derived from financial data extracted from the Danish Energy Agency technology data catalogue [20]. It is worth noting that a cheap battery scenario is considered. The technology costs assumptions are summarized in Table 1

In this case study, the primary objective function considered is the net present value of capital expenditures (NPV/CAPEX). The resulting optimal designs are then compared with

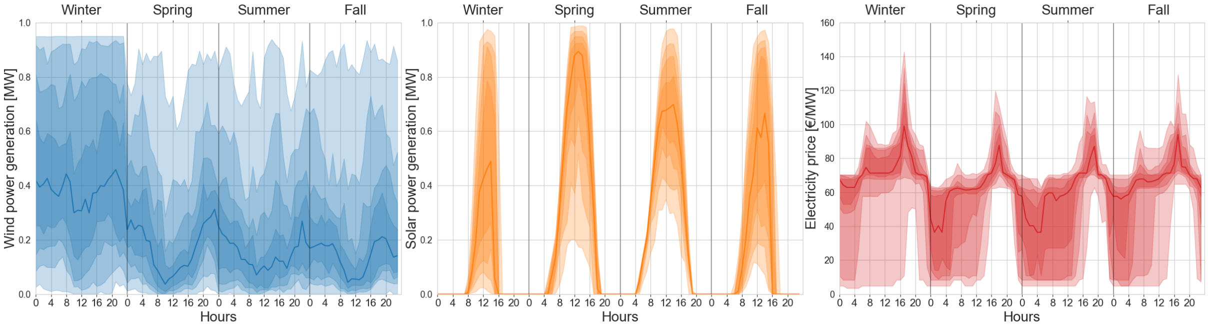

Figure 5. Hourly median and quantiles per season of a 1 MW wind turbine power generation (left), 1 MW installed PV power generation (middle), and electricity price (right) **in the average wind and solar site situated in Germany.** Wind power generation considers the following specifications: clearance = 49, specific power = 321, rated power = 5, wind power density = 7. Solar plant generation considers the following panel specifications: tilt angle = 48, azimuth angle= 210. Darker colours represent higher probability.

Table 1. Technology costs considered in the optimization.

Wind technology costs	
Wind turbine cost	640 k€/MW
Wind civil works cost	80 k€/MW
Wind fixed operation/maintenance cost	12.6 k€/MW/year
Wind variable operation/maintenance cost	1.35 k€/MWh
Solar technology costs	
Solar PV cost	110 k€/MW
Solar hardware installation cost	100 k€/MW
Solar inverter cost	20 k€/MW
Solar fixed operation/maintenance cost	4.5 k€/MW
Battery technology cost	
Battery energy cost	45 k€/MWh
Battery power cost	16 k€/MW
Battery BOP/installation/commissioning cost	18 k€/MW
Battery control system cost	4.5 k€/MW

plant designs that aim to minimize the levelized cost of energy (LCOE).

In the sizing optimization, NPV/CAPEX is the primary metric for economic evaluation instead of the internal rate of return (IRR) because the latter is not defined when NPV is negative, which is the case for a significant portion of the design space considered.

4. Results and discussion

The detailed sizing results based on NPV/CAPEX and LCOE in the three different locations are presented Table 2.

In the windy site situated in Denmark, the NPV/CAPEX optimal design is a hybrid power plant consisting of 275 MW of wind, 155 MW of solar, and 35 MW of battery with a storage duration of 3 hours. Minimizing LCOE, on the hand, recommends installing a 310 MW wind power plant with 27 MW of PV.

In France's sunny site, the NPV/CAPEX-based design resulted in a hybrid power plant comprising of 338 MW of solar and 37 MW of battery with a 2-hour storage duration, minimizing LCOE leads to a design made up of only 329 MW of PV with no battery installation. Similar to the sunny site results, the sizing optimization in the third site in Germany led to a hybrid power plant consisting of 380 MW of solar and 91 MW of battery with a storage duration of 2 hours when maximizing NPV/CAPEX, LCOE-based design consists of only 317 MW of PV.

In all three sites, optimizing NPV/CAPEX resulted in a hybrid power plant with a higher total capacity than the optimal plant obtained by minimizing LCOE. When the objective is set to NPV/CAPEX, the solver aims to maximize the overall profitability of the project, rather than just the cost of energy production. By integrating battery storage into the design of a hybrid power plant, the profitability of the project can be significantly improved.

The inclusion of batteries enables the shifting of energy production from periods of low electricity prices to periods of high electricity prices, thereby maximizing revenue. Additionally, batteries allow for over-planting, as excess energy produced during peak production can be stored and used during periods of low energy production. This avoids the need to curtail energy production during peak periods, which ultimately increases the overall efficiency of the plant. Overall, incorporating battery storage in the design of a hybrid power plant leads to a more efficient and profitable project. This is can be seen in Table 2, where the inclusion of battery in the design led to a higher NPV in all sites. In the first site, a 2.7 % increase in NPV was achieved, in the second a 5.8 % increase, and in the third site a 13 % increase.

Table 2 shows that the internal rate of return (IRR) of the project is similar for both the NPV/CAPEX optimization and the LCOE minimization, which is contrary to what would be expected. This result is due to the high electricity prices used in the analysis, resulting from the current situation in Ukraine which has disrupted energy markets. Consequently, a very favorable business case can already be achieved by considering LCOE as the objective function, where the solver aims to install the cheapest technology considering the available weather resources. If a data set with lower electricity prices were used, the impact of installing batteries would be more significant, leading to a greater difference in IRR between the NPV/CAPEX optimization and the LCOE minimization. Furthermore, if power purchase agreements (PPA) were considered instead of spot electricity markets, the impact on IRR would be even more pronounced between the two designs.

Figure 6 presents the hourly median and the 5^{th} and 95^{th} quantiles of the revenue per season in the windy site, for both the NPV/CAPEX and LCOE based designs. Darker colors indicate higher number of occurrences. The NPV/CAPEX optimal design generally generates more revenue than the LCOE based design in all seasons. This difference is particularly noticeable during the middle of the day, especially in the summer and spring seasons. The higher revenue generated by the NPV/CAPEX design can be attributed to the greater amount of PV installed, which allows it to take more advantage of high irradiance during the middle of the day.

Figure 7 indicates that the revenue generated by the NPV/CAPEX and LCOE designs are quite similar in the sunny site. As can be seen in Table 2, both designs have a similar PV installation. However, the NPV design generates a slightly higher revenue than the LCOE design, particularly during peak electricity price periods, thanks to the battery's ability to shift power to these periods. The 95^{th} quantile reveals that there are occurences in which the NPV/CAPEX design produces a greater revenue when the electricity price spikes, particularly between 4 pm and 8 pm, refer to Figure 4. For example, when the electricity price surges between 4 pm and 6pm in the fall, the median revenue is much higher with the NPV/CAPEX design.

Figure 8 presents the hourly median of the revenue per season for the German site. This plot reinforces the findings from the previous figure. The fall season provides a good example of the revenue differences between the LCOE and NPV designs. At the beginning of the day, the LCOE design generates slightly higher revenue than the NPV design. However, during peak electricity price periods, the NPV design generates more revenue thanks to the battery's ability to charge during low-price hours and discharge during high-price hours to maximize profits.

Table 2. Technology costs considered in the optimization.

Country	**Denmark**		**France**		**Germany**	
Site description	**Good Wind**		**Good Solar**		**Average Solar & Wind**	
Latitude	55.23		44.42		49.31	
Longitude	11.94		4.23		10.77	
Elevation	107		204		442	
Optimization function	**NPV**	**LCOE**	**NPV**	**LCOE**	**NPV**	**LCOE**
Clearance (m)	49	54	29	10	33	25
Specific power (m^2/W)	321	316	276	330	246	234
Rated power (MW)	5	5	1	1	3	4
Number of wind turbines	55	62	0	0	0	0
Wind power density (MW/km^2)	7	6	6	5	7	5
Solar power (MW)	155	27	338	329	380	317
Surface tilt (degs)	46	17	44	38	48	37
Surface azimuth (degs)	210	158	210	210	210	210
DC/AC Ratio	1.51	1.52	1.59	1.59	1.66	1.86
Battery power (MW)	35	0	37	0	91	0
Battery storage duration (h)	3	1	2	1	2	1
NPV over CAPEX	0.94	0.94	0.96	0.96	0.89	0.88
NPV (Meuro)	304.54	296.72	164.48	155.9	176.55	155.06
LCOE (Euro/MWh)	21.16	20.42	21.75	21.27	27.29	26
CAPEX (Meuro)	323.61	315.27	171.02	163.02	198.65	176.6
OPEX (Meuro)	6.16	6	2.41	2.35	2.84	2.66
Grid (MW)	300	300	300	300	300	300
Wind (MW)	275	310	0	0	0	0
Solar (AC MW)	155	27	338	329	380	317
Solar (DC MW)	233.8	41.14	536.13	521.5	632.13	590.84
Battery Power (MW)	35	0	37	0	91	0
Battery Energy (MWh)	105	0	74	0	182	0
Total curtailment (GWh)	40.39	5.14	7.02	12.93	16.82	4.48
Rotor diameter (m)	140.83	141.94	67.92	87.84	124.61	147.53
Hub height (m)	119.41	124.97	62.96	53.92	95.3	98.76
Optimisation time (min)	75.51	62.77	21.17	40.66	40.07	47.82

This finding highlights the importance of considering not only the initial investment costs but also the potential revenue benefits of storage in renewable energy projects.

5. Conclusion

The study examined the potential of hybrid power plants in European markets by applying a hybrid sizing algorithm to three locations with varying weather resources. The results are encouraging and indicate that hybrid power plants have promising prospects in European markets. The study evaluated two objective functions, NPV/CAPEX and LCOE. While NPV/CAPEX favors hybridization to maximize revenue generation, LCOE focuses on installing the cheapest technology based on weather resources. Overall, the study highlights the potential of hybrid power plants in Europe and provides valuable insights into the importance of considering multiple financial metrics for optimal plant sizing.

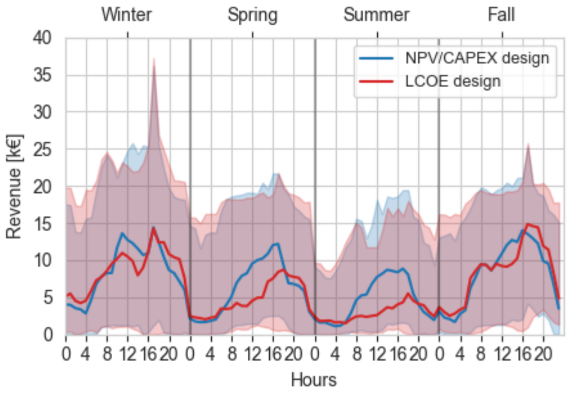

Figure 6. Hourly median and 5^{th} and 95^{th} quantiles of the revenue per season **in the good wind site in Denmark.**

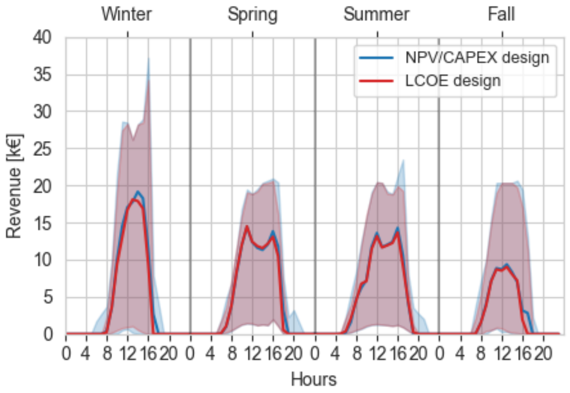

Figure 7. Hourly median and 5^{th} and 95^{th} quantiles of the revenue per season **in the good solar site in France.**

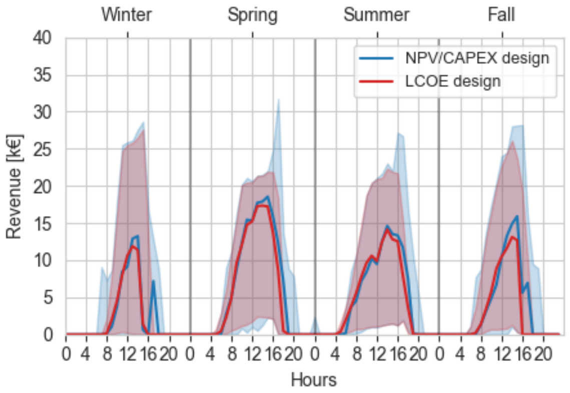

Figure 8. Hourly median and 5^{th} and 95^{th} quantiles of the revenue per season **in the average wind and solar resources in Germany.**

References

[1] Hybrid renewable power plants make a good business case but need clearer legislation to become more widespread, Oct 2020. https://windeurope.org/newsroom/news/hybrid-renewable-power-plants-make-a-good-business-case/.

[2] Katherine Dykes, Lena Kitzing, Mattias Andersson, Cristian Pons-Seres de Brauwer, and Helena Canét. Beyond lcoe: New assessment criteria for evaluating wind energy r&i. In *SETWind workshop*, 2020.

[3] Katherine Dykes, Jennifer King, Nicholas DiOrio, Ryan King, Vahan Gevorgian, David Corbus, Nate Blair, Kate Anderson, Greg Stark, Craig Turchi, et al. Opportunities for research and development of hybrid power plants. Technical report, National Renewable Energy Lab.(NREL), Golden, CO (United States), 2020.

[4] Charles Tripp, Darice Guittet, Jennifer King, and Aaron Barker. A simplified, efficient approach to hybrid wind and solar plant site optimization. *Wind Energy Science*, 7(2):697–713, 2022.

[5] Darice Guittet, P. J. Stanley, Bill Hamilton, Jen King, and Aaron Barker. Hopp - hybrid optimization and performance platform.

[6] Homer pro help manual, April 2019. https://www.homerenergy.com/products/pro/docs/3.13/index.html.

[7] Flexiq: Design, operations, and fleet management solutions to optimize a hybrid project's customer value. https://www.ge.com/renewableenergy/hybrid/flexiqDISPATCHER.

[8] Robert Idel. Levelized full system costs of electricity. *Energy*, 259:124905, 2022.

[9] Juliet Simpson, Eric Loth, and Katherine Dykes. Cost of valued energy for design of renewable energy systems. *Renewable Energy*, 153:290–300, 2020.

[10] Eric Loth, Chris Qin, Juliet G Simpson, and Katherine Dykes. Why we must move beyond lcoe for renewable energy design. *Advances in Applied Energy*, 8:100112, 2022.

[11] Juan Pablo Murcia Leon, Hajar Habbou, Kaushik Das, Rujie Zhu, and Mikkel Friis-Møller. Dtuwindenergy/hydesign: Release of v1.0.3, January 2023.

[12] Justin S Gray, John T Hwang, Joaquim RRA Martins, Kenneth T Moore, and Bret A Naylor. Openmdao: An open-source framework for multidisciplinary design, analysis, and optimization. *Structural and Multidisciplinary Optimization*, 59:1075–1104, 2019.

[13] Hans Hersbach, Bill Bell, Paul Berrisford, Shoji Hirahara, András Horányi, Joaquín Muñoz-Sabater, Julien Nicolas, Carole Peubey, Raluca Radu, Dinand Schepers, et al. The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049, 2020.

[14] Juan Pablo Murcia, Matti Juhani Koivisto, Graziela Luzia, Bjarke T Olsen, Andrea N Hahmann, Poul Ejnar Sørensen, and Magnus Als. Validation of european-scale simulated wind speed and wind generation time series. *Applied Energy*, 305:117794, 2022.

[15] Katherine Dykes, Andrew Ning, Ryan King, Peter Graf, George Scott, and Paul S Veers. Sensitivity analysis of wind plant performance to key turbine design parameters: a systems engineering approach. In *32nd ASME Wind Energy Symposium*, page 1087, 2014.

[16] Mohamed Amine Bouhlel, John T Hwang, Nathalie Bartoli, Rémi Lafage, Joseph Morlier, and Joaquim RRA Martins. A python surrogate modeling framework with derivatives. *Advances in Engineering Software*, 135:102662, 2019.

[17] Global wind atlas map. https://globalwindatlas.info/en.

[18] Global solar atlas map. https://globalsolaratlas.info/map.

[19] Frauke Wiese, Rasmus Bramstoft, Hardi Koduvere, Amalia Pizarro Alonso, Olexandr Balyk, Jon Gustav Kirkerud, Åsa Grytli Tveten, Torjus Folsland Bolkesjø, Marie Münster, and Hans Ravn. Balmorel open source energy system model. *Energy strategy reviews*, 20:26–34, 2018.

[20] Technology data for renewable fuels. https://ens.dk/sites/ens.dk/files/Analyser/technology-data-for-renewable-fuels.pdf.