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Modelling offshore wind-battery hybrid systems to evaluate flexibility in the Dutch power markets

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Contents

Executive summary

Offshore wind will become the dominant power source by 2030 with at least 11.5 GW installed capacity, with current plans exploring between 20 and 40 GW of additional offshore wind capacity to be installed. Flexibility options must be developed hand-in-hand with the massive upscale of wind energy deployment, including both conversion and storage technologies.

The ability to time-shift the moment of trading in the power market is seen as an essential development for offshore wind. This can provide flexibility options for grid stability, increasing baseload generation and thus, securing supply. Large-scale battery storage, combining both short and long duration energy storage, can be a key enabler for future wind deployment, since it will reduce renewable energy curtailment, help frequency regulation, facilitate flexible ramping and black start services

The emergence of hybrid power plants as a single asset bidding in the power market have required modellers to adapt and implement new methodologies. Research is required for model implementation and adaptation, to evaluate their impact on system perspective and the wind business case. This study models the future power market behaviour by 2030 following the targets of the Climate Agreement to evaluate the flexibility requirements and the role of connecting the wind with battery at large scale. A reference case, where the battery and wind farm are unconnected is compared with a hybrid asset, where the battery stores the power from the wind farm as a smart system.

In addition, mathematical optimization is performed to estimate the optimum design of the battery in connection with a wind farm (1.4 GW capacity, as Borssele wind farm of case study), considering as an objective function the maximization of the profit. A case with a fixed battery capacity of 1 GWh is shown to already mitigate 30% of the curtailment loss, which is all power above 1300 MW in this case. This curtailment reduction combined with the time-shifting potential introduced by the battery also leads to an increase in revenue of approximately 4 M€ with respect to the base case. This result yields an allowable margin for the battery cost of roughly 100 M€, assuming a project lifetime of 25-30 years. With a 1 GWh battery capacity installed, this translates to an equivalent cost of 100 €/kWh, close to the expected threshold for price competitive battery storage.

1 Introduction

The commitment of the Netherlands to a climate neutral society by 2050 stipulates 100% renewable electricity generation and 95% reduction of its greenhouse gas emissions compared to the 1990 levels (Climate Law, Dutch NECP [1] and Dutch long-term strategy [2]). Offshore wind will become the dominant power source by 2030 with at least 11.5 GW installed capacity in the Dutch North Sea and will meet more than 50% of electricity demand by 2050 with an installed capacity of 60-75 GW [1], [3].

The North Sea Agreement includes more zones for offshore wind energy, a clause to explore the scope for between 20 and 40 GW of additional offshore wind capacity to be installed over the 11.5 GW mentioned earlier. In the North Sea Programme 2022–2027, this translates into a brief for an additional 27 GW of offshore wind energy. Together with the 11.5 GW, this will be enough to reach the minimum of the 38-72 GW total offshore wind capacity target.

1.1 Hybrid systems in the power market

From the perspective of a business case, dropping technology costs and increasing market integration makes wind energy investments increasingly competitive, which in turn will lead to subsidy-free operation. Increased risk of investing in renewables due to price volatility may translate into higher capital costs and discourage future investments [4] [5].

The success of the energy transition ultimately depends on the harmonious cooperation of many different actors. Flexibility options must be developed hand-in-hand with the massive upscale of offshore wind deployment [6]. National targets and infrastructure roadmaps therefore include both conversion and storage technologies; by 2050, a total flexible capacity between 110-135 GW, combining electrolysis (~60-75 GW) and battery storage technologies (~50-60GW) is forecasted [7], [8].

The ability to shift in time the moment of trading in the power market is seen as an essential development for offshore wind. This can provide flexibility options for grid stability [9], increasing baseload generation and thus, securing supply.

Battery storage systems are a potential solution due to their unique capability to quickly absorb, hold and then reinject electricity. Large-scale battery storage, combining both short and long duration energy storage (LDES) can be key enablers for future wind deployment, since it will reduce renewable energy curtailment [10], help frequency regulation, facilitate flexible ramping and black start services [11]; being essential to the secure operation of a fossil fuel-free grid [12], [13]. A recent report on the role of LDES [14] describes how this technology can be integrated in the market and provide a service. Novel LDES technologies can be used in a range of flexibility durations, making them suitable for different applications (**Figure 1**).

● Solution ◌ Partial solution

Flexibility duration	Power system challenge	Dispatchable generation	Grid rein-forcement	Curtailment or feed-in management	Li-ion batteries	LDES	Demand-side response
Intraday	Intermittent daily generation	●		●	●	●	●
	Reduced grid stability	●			●	●	◌
Multiday, multiweek	Multi-day imbalances	●	◌	◌	◌	●	
	Grid congestion	◌	●	●	◌	●	
Seasonal duration	Seasonal unbalances	●	●			●	
	Extreme weather events	●				●	

Energy storage form	Technology	Market readiness	Max deployment size, MW	Max nominal duration, Hours	Average RTE[1] %
Mechanical	Novel pumped hydro (PSH)	Commercial	10–100	0–15	50–80
	Gravity-based	Pilot	20–1,000	0–15	70–90
	Compressed air (CAES)	Commercial	200–500	6–24	40–70
	Liquid air (LAES)	Pilot (commercial announced)	50–100	10–25	40–70
	Liquid CO_2	Pilot	10–500	4–24	70–80
Thermal	Sensible heat (eg, molten salts, rock material, concrete)	R&D/pilot	10–500	200	55–90
	Latent heat (eg, aluminum alloy)	Commercial	10–100	25–100	20–50
	Thermochemical heat (eg, zeolites, silica gel)	R&D	na	na	na
Chemical	Power-to-gas-(incl. hydrogen, syngas)-to-power	Pilot (commercial announced)	10–100	500–1,000	40–70
Electrochemical	Aqueous electrolyte flow batteries	Pilot/commercial	10–100	25–100	50–80
	Metal anode batteries	R&D/pilot	10–100	50–200	40–70
	Hybrid flow battery, with liquid electrolyte and metal anode	Commercial	>100	25–50	55–75

Figure 1 (top) Flexibility duration and potential market in which the batteries can play a crucial role together with other flexibility providers (bottom) key LDES storage types and parameters. RTE is the round trip efficiency. (1) Power-to-power only. RTEs of systems discharging other forms of energies such as heat can be significantly higher (*Source of figure McKinsey and Co* [14]).

1.2 Gap and research goals

The emergence of hybrid power plants as one single asset bidding in the power market have required modellers to adapt and implement new methodologies. Research is required both for model implementation and adaptation and to evaluate their impact on system perspective and from the wind business case.

Previous studies focusing on developing a long-lasting offshore wind business case in the Dutch Energy Transition by 2050 [4], [15] concluded that flexibility is a necessary source to allow a complete utilization of variable RES (vRES) generation and adequacy of the system. However, a larger flexible demand requires larger supply from conventional assets, characterized by high marginal costs, resulting in higher market prices and higher values for vRES. Moreover, demand variation impacts prices: a larger electricity demand requires a larger supply from conventional assets, increasing prices. With higher electricity demand, the value of offshore wind generated electricity decreases, as a larger share is needed to balance the increased demand, and therefore a smaller share is available for storage in flexible assets. Furthermore, changes in the demand also affects offshore wind utilization and flexibility: lower the electricity demand, lower the offshore wind utilization and higher the flexibility needed to maintain the system stability. ETS CO_2 costs affect prices and vRES value, due to the increase in marginal prices of gas assets. However, gas assets production drops if their marginal costs become more expensive than biomass. Same behavior observed for battery, higher prices lowers their usage.

Therefore, from the perspective of a business case for offshore wind in the future marketplace, it was possible to conclude that:

- Future electricity prices are sensitive to abovementioned specific market drivers.
- To achieve a climate neutral system, high penetration of RES is required in conjunction with flexibility. Such a combination increases future electricity prices, introduces higher volatility and risk exposure.
- From a business case point of view, offshore wind is vulnerable to these changes. Currently, profits for offshore wind rely on subsidy schemes. The era of zero-subsidies has arrived and offshore wind developers will need to look to other ways of increasing net profits. Increasing offshore wind profit by producing green hydrogen or storing the electricity for a later moment in time are promising combinations

The paper concluded that further research is needed in multi objective optimization to maximize both offshore wind profits and conversion and storage utilization. The necessity for balancing both the offshore wind profits and the capacity or utilization will be a necessary problem to be solved for an efficient future energy system.

Thus, the goals of this study are

1. **Representation of the Dutch power market by 2030 and estimating the amount of flexibility required to integrate offshore wind energy without endangering the security of supply.**
2. **An optimum battery design to improve the business case for wind, considering 2030 market conditions and grid infrastructure.**
3. **Power market model implementation to represent a hybrid system of wind farms connected to a battery as a combined asset bidding in the power market.**

The overall approach of this study consists of modelling the future power market behaviour by 2030 following the targets of the Climate Agreement to evaluate the flexibility requirements and the impact of connecting large amounts of offshore wind with batteries. Secondly, mathematical optimization is performed to estimate the optimum design of the battery in connection with an offshore wind farm considering as an objective function the maximization of the profit and the utilization of the battery. Finally, the optimum compound asset (battery and wind connected as a single asset) is modelled in a power market simulation tool. In this model, the asset places bids in the day ahead market over a one year simulation period, and the potential business case for such compound assets is investigated.

2 Approach

2.1 Power market model implementation of hybrid power systems

2.1.1 Electricity power model configuration

The Dutch electricity market is modelled using the EYE (ElectricitY market price Evolution simulator) model [16]. The EYE model is an electricity system simulator which can analyse electricity prices given certain scenario inputs (asset specifications, commodity prices, expected demand etc).

The order of the setting technologies are: must run assets enter first in the bid, and are located on the left side of the price curve (See Figure 2). Next, near or zero price technologies enter due to RES supply (0 €/MWh and 1.6 €/MWh are the default marginal costs for solar and wind energy onshore and offshore). Conventional fossil-fuelled assets and biomass with higher operating costs are on the other end of the curve. Generally, flexible assets are included in the middle range of the price duration curve and are characterized by high prices. In the EYE model if flexible assets are not completely fed by RES, their operating costs are high due to being fed by conventional energy sources. The configuration of this model is explained further in this section.

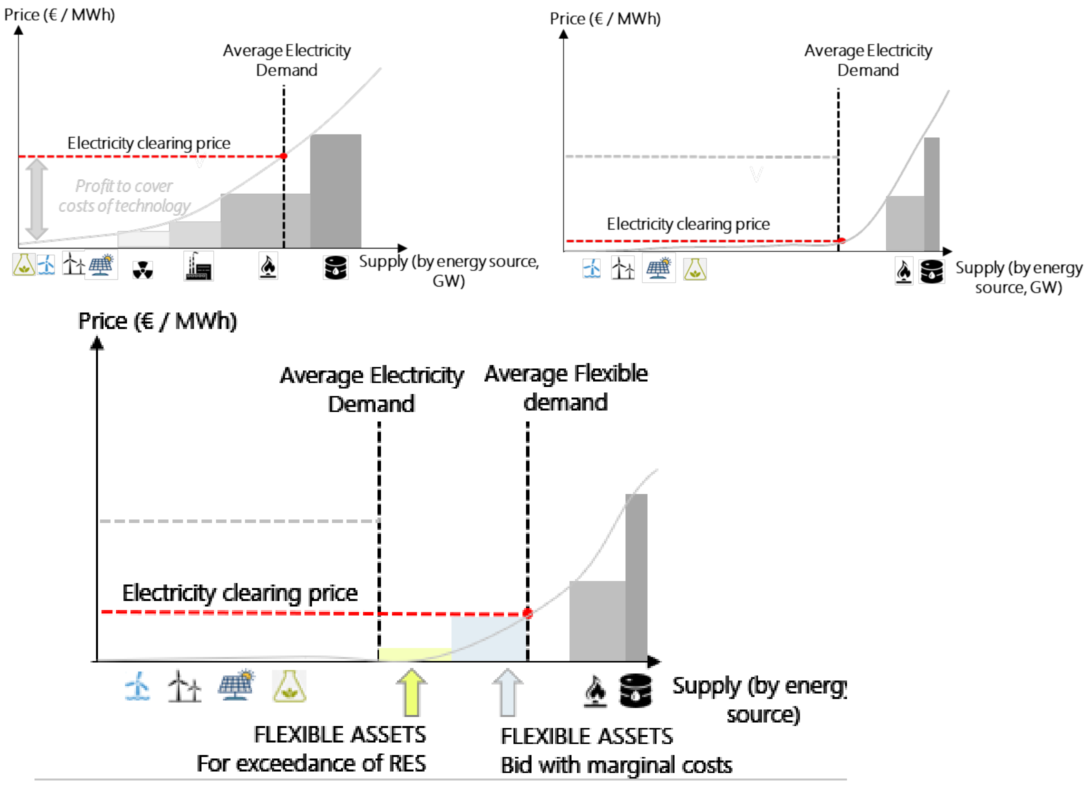

Figure 2 Merit order effect in the power market under a) current renewable energy sources (RES) portfolio (2020); b) high RES penetration without flexible options and c) high penetration of renewables together with flexibility options in the power market

Inputs

- Renewable and non-renewable assets are configured in the model by defining the among others, the type and name of the asset, its commissioning and decommissioning dates, power output and efficiency.
- A demand profile based on hourly timesteps is defined
- Fuel name and fuel prices (in €/MWh) are defined and selected in various types of assets, along with their marginal costs
- Simulation parameters such as start and stop date should be defined

Outputs

- The clearing price of electricity is calculated at each hourly timestep in the simulation period according to the merit order logic
- The utilisation of assets at every timestep is calculated as output.
- For special assets such a battery, the amount of electricity stored in the battery at each hourly timestep is calculated as output

2.1.2 Compound (or hybrid) wind-battery asset

To implement hybrid power systems in the EYE model, the concept of compound assets are developed. A compound asset consists of a wind farm connected directly to a battery. It operates as a single actor in the power market with the aim to provide flexibility to the electricity generated. The compound asset stores excess power in times of low market prices by charging the battery and selling power to the market when prices are higher. The characteristics that define the battery implemented in the model are:

- Battery capacity: the total energy (in MWh) that the battery can store
- Maximum charge & discharge rate (in MW) each hour
- Fill level: (in %), the amount of charge in the battery compared to the battery capacity. If E_{bat} is the rated battery capacity and E_t is the current charge in the battery, the fill level F_t^{bat} is given by:

$$F_t^{bat} = E_t/E_{bat} \tag{1}$$

- Forecast window length: the length of time for which the battery is assumed to have a knowledge of the market prices.
- Battery operational cost: the marginal cost of operating the battery in €/MWh

Interaction between wind farm and battery

A choice between two strategies governs the interaction between the wind farm and the battery. The available choices of strategies to select from are 'Ratio' and 'Threshold'.

Strategy Ratio:

In the strategy 'Ratio', the wind farm will store a fraction of the power it produces in the battery at each timestep, provided there is sufficient capacity remaining in the battery. The remaining 'non-stored' energy from the wind farm will be available for the wind farm to sell in the electricity market.

Therefore, if P_t^{WF} is the power produced by the wind farm at a particular timestep, then:

$$P_t^{bat} = P_t^{WF} * Ratio \tag{2}$$

$$P_t^{market} = P_t^{WF} - P_t^{bat} \quad (3)$$

where P_t^{market} is the amount of wind energy available for trading in the market and P_t^{bat} is the amount of energy stored in the battery during that particular timestep, keeping in mind the condition:

$$F_t^{bat} < F_{max}^{bat} \; and \; F_t^{bat} > F_{min}^{bat} \quad (4)$$

where F_t^{bat} is the current battery fill level, F_{max}^{bat}, F_{min}^{bat} are the maximum and minimum battery fill levels.

Consider, a 700 MW wind farm connected with a battery under strategy ‘Ratio’ with a value of 0.1. Suppose that based on the wind speeds in the first four hours of operation on a certain day, the wind farm produces a total power of 300 MW, 400 MW, 500 MW and 600 MW. Due to the strategy ‘Ratio’, 30 MW, 40 MW, 50 MW and 60 MW will be stored in the battery, provided the fill level of the battery does not exceed the maximum allowed limit, and the remaining ’non-stored’ energy will be available for the wind farm to sell in the electricity market.

Strategy Threshold:

In the strategy ‘Threshold’, provided there is sufficient capacity remaining in the battery, only the amount of energy above a certain user-defined threshold is stored in the battery. The remaining ’non-stored’ energy from the wind farm will be available for the wind farm to sell in the electricity market.

Therefore, if the user defined threshold ($E_{threshold}^{bat}$) is less than the power produced by the wind farm at a particular timestep (P_t^{WF}) then:

$$P_t^{bat} = P_t^{WF} - E_{threshold}^{bat} \quad (5)$$

and

$$P_t^{market} = E_{threshold}^{bat} \quad (6)$$

where P_t^{market} is the amount of wind energy available for trading in the market and P_t^{bat} is the amount of energy stored in the battery during that particular timestep.

However, if the user defined threshold ($E_{threshold}^{bat}$) is equal to or greater than the power produced by the wind farm (P_t^{WF}) at a particular timestep then:

$$P_t^{bat} = 0 \quad (7)$$

And

$$P_t^{market} = P_t^{WF} \quad (8)$$

where P_t^{market} is the amount of wind energy available for trading in the market and P_t^{bat} is the amount of energy stored in the battery during that particular timestep.

For instance, with the same 700 MW wind farm and four hours of power output as in the above example (300 MW, 400 MW, 500 MW and 600 MW), a threshold of 450 MW will mean that the battery will store 0 MW, 0 MW, 50 MW and 150 MW during the four hours of operation and the remaining ’non-stored’ energy will be available for the wind farm to sell in the electricity market.

Interaction between compound wind-battery asset and the market

The bidding behavior of the battery in the market is based on identifying potential buy-sell pairs within a forecast window length. The forecast window length is the future duration of time for which the battery is aware of the market prices. In a day ahead market, for instance, where market prices are known for the next day, the forecast window will be 24 hours.

In the EYE model, the batteries are assumed to have perfect knowledge of the value of the price by way of a implementing a virtual run, where a scenario is pre-simulated without the participation of the battery. Once the market prices for the length of a forecast window are known, the following steps are simulated in order for a battery to interact with the market:

- The decision to charge/discharge the battery is made every X hours (which is equal to the forecast window length). No new decisions are made in between these scheduled forecast window length blocks
- If the fill level of the battery is greater than 80%, then the battery would discharge at the maximum discharge rate for the current block at any price.
- If the fill level of the battery is lesser than 20%, then the battery would charge for the current block at any price at the maximum charge rate for the current block at any price
- If the fill level of the battery is in between 20% and 80%, and if the difference between the highest and lowest market prices in the forecast window is greater than the battery operational cost, the battery will charge (buy) at the lowest clearing price and discharge (sell) at highest clearing price in the window.

For example, if the battery operational cost is 50 €/MWh, and the forecast window shows market prices of 36 €/MWh, 48 €/MWh, 60 €/MWh and 90 €/MWh , the battery would buy at 36€/MWh and sell at 90 €/MWh.

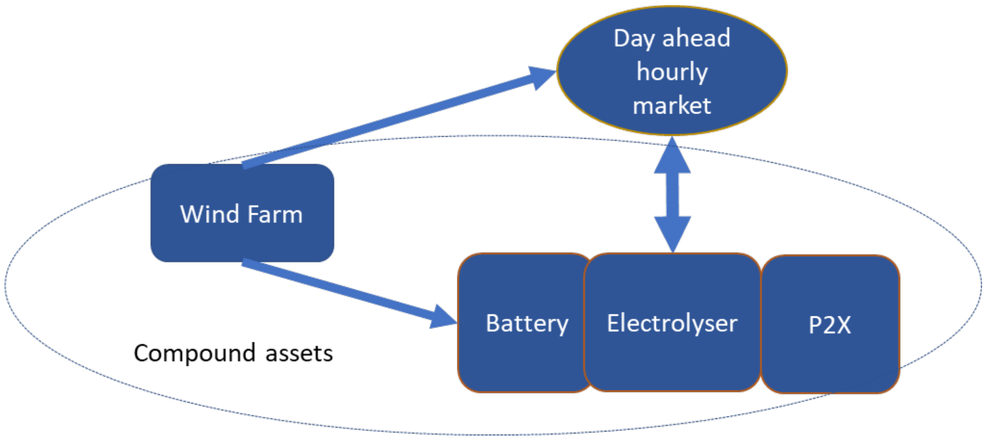

Figure 3 Examples of hybrid systems as a single actor bidding in the power market

Besides the combination of a wind farm and battery, the EYE model will be extended to include future combinations of hybrid system involving electrolysers and power-to-X assets.

2.2 Battery capacity and power optimization

In preparation for modelling the market interaction of the combined wind and battery asset, it is first necessary to determine the required battery capacity. Such an optimization is useful in order to determine the best balance between cost invested in storage capacity, and additional revenue generated due to the ability to prevent curtailment, or time-shift energy and sell at a higher price later, subject to expected market conditions.

In order to do this, a profit maximization optimization for these expected market conditions is performed, with the objective function defined by (9) and (10).

Maximize:

$$\sum_{t=0}^{T}(\mathcal{P}_t) - C_{eq} \tag{9}$$

$$\mathcal{P}_t = \mathcal{R}_t - \mathcal{C}_t \tag{10}$$

where $\mathcal{P}_t$, $\mathcal{R}_t$ and $\mathcal{C}_t$ are the profit, revenue and cost at time t, respectively, and C_{eq} is the equivalent yearly Capital Expenditure (CAPEX), as defined in (11), where E_{bat} is the rated battery capacity, $\lambda_{b,unit}$ is the battery unit cost, and L_{bat} is the expected battery lifetime.

$$C_{eq} = \frac{E_{bat} \cdot \lambda_{b,unit}}{L_{bat}} \tag{11}$$

The revenue and cost are calculated using (12) and (13), respectively, where P_t^e is the exported power, λ_t is the market price at time t, Δt is the timestep, P_t^{WF} is the wind farm power, λ_{LCOE} is the levelized cost of the electricity produced by the wind farm, P_{curt} is the curtailed power, and μ_{curt} is a penalty factor (cost) associated with curtailed power. The battery cost $\mathcal{C}_{bat}$ is defined as in (14), where $P_t^{b,in}$ and $P_t^{b,out}$ are the battery charging and discharging power, respectively, with $\lambda_{b,ch}$ and $\lambda_{b,dis}$ the respective cost associated with charging and discharging.

$$\mathcal{R}_t = P_t^e \cdot \lambda_t \cdot \Delta t \tag{12}$$

$$\mathcal{C}_t = (P_t^{WF} \cdot \Delta t \cdot \lambda_{LCOE}) + \mathcal{C}_{bat} + P_t^{curt} \cdot \mu_{curt} \tag{13}$$

$$\mathcal{C}_{bat} = \left(P_t^{b,in} \cdot \Delta t \cdot \lambda_{b,ch}\right) + \left(P_t^{b,out} \cdot \Delta t \cdot \lambda_{b,dis}\right) \tag{14}$$

The charging and discharging behaviour of the battery is further described by calculation of the battery fill level in (15) and (16), limitations to the fill level in (17) and (18), and limitations to the charging and discharging power in (19) and (20).

$$F_t^{bat} = SOC_{init} \cdot E_{bat}, \qquad t = 0 \tag{15}$$

$$F_t^{bat} = F_{t-1}^{bat} + \left(P_t^{b,in} \cdot \Delta t \cdot \eta_{ch}\right) - \left(P_t^{b,out} \cdot \Delta t \cdot \eta_{dis}\right), \qquad \forall t > 0 \tag{16}$$

$$F_t^{bat} \geq E_{bat} \cdot 0.1, \qquad \forall t \tag{17}$$

$$F_t^{bat} \leq E_{bat} \cdot 0.9, \qquad \forall t \tag{18}$$

$$P_t^{b,in} \leq 0.5 \cdot E_{bat}, \qquad \forall t \tag{19}$$

$$P_t^{b,out} \leq 0.5 \cdot E_{bat}, \qquad \forall t \tag{20}$$

where F_t^{bat} is the battery fill level, SOC_{init} is the initial state-of-charge (SOC) of the battery, and η_{ch} and η_{dis} are the charging and discharging efficiencies.

The power balance of the entire system is described by (21).

$$P_t^{WF} + P_t^{b,out} = P_t^{e} + P_t^{b,in} + P_{curt}, \qquad \forall t \tag{21}$$

This system is also visualized in Figure 4 below, showing the power flow, revenues and cost.

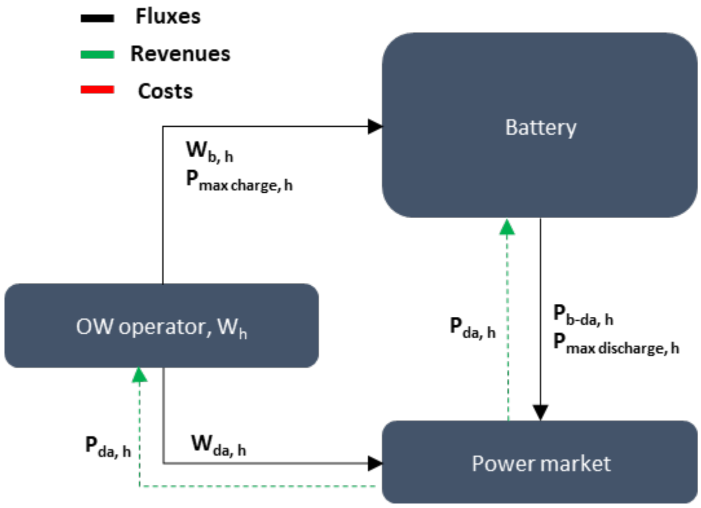

Figure 4: Overview of the power, revenue and cost flow of the optimized system, as described by (9)-(21).

Additionally, the possibility to optimize the utilization rate of the export cable instead of the profit can be added by replacing (9) with (22).

Maximize:

$$\sum_{t=0}^{T} P_t^{e} \tag{22}$$

The above optimization problem uses the battery capacity as a variable, so it will be one of the results of the solution (next to the optimal profit). Alternatively, it is possible to use the battery charging and discharging as a variable, if the capacity is known. This is done by replacing (19) and (20) by (23) and (24).

$$P_t^{b,in} \leq 0.5 \cdot P_{ch}, \qquad \forall t \tag{23}$$

$$P_t^{b,out} \leq 0.5 \cdot P_{dis}, \qquad \forall t \tag{24}$$

where P_{ch} and P_{dis} are the maximum charging and discharging power, respectively.

An overview of the input data for the case study that uses this optimization is presented in Table 1 below. Additionally, an overview of all symbols used to define the optimization model can be found in Appendix A.

Table 1: List of values used in the case study for the input parameters.

Parameter	Value	Unit	Parameter	Value	Unit
E_{bat}	1000	MWh	$\lambda_{b,ch}$	$0.875 \cdot 10^{-3}$	€/kWh
$\lambda_{b,unit}$	100	€/kWh	$\lambda_{b,dis}$	$0.547 \cdot 10^{-3}$	€/kWh
L_{bat}	30	year	SOC_{init}	0.5	-
Δt	1	hour	η_{ch}	0.95	-
λ_{LCOE}	50	€/MWh	η_{dis}	$(1/0.95)$	-
μ_{curt}	0.01	€/kWh			

2.3 Scenarios, assumptions and case study

2.3.1 Reference scenario selected

The scenario selected and assumptions are built on the Dutch national climate scenario called the Dutch Integrated National Energy and Climate Plan (NECP) 2021-2030 [1]. This is based on the Climate and Energy Report (KEV) 2020 by the Netherlands Environmental Assessment Agency (PBL).

The national CO_2 targets defined by the Netherlands of an emissions reduction of 49% by 2030 compared with 1990, proposed in the Coalition Agreement, means a reduction of approximately 71 Mton of CO_2 equivalents by 2030 compared with an unchanged policy [17]. The following (long-term) objectives for 2030.

Models used for this analysis are existing TNO Energy System Models (ESM) and Power System Models (PSM) configured and set up under the scenarios selected. Firstly, the **OPERA ESM**[1] [18] has been run under the NECP scenario by 2030 and then, its output (such as the hourly time series of demand for electricity and flexibility, the imports and exports) has been fed in to the **EYE PSM**[2] model [19] to obtain future electricity prices and the merit order effect. Additionally, the output of the future electricity prices from the EYE model have been also compared with the results of the **COMPETES PSM**[3] [20] under the same scenarios with the aim to have a robust range of uncertainties and range of trends and behaviour of the future power market where the analysis of the results can be found in [4].

Table 2 Considered main drivers in the NECP by 2030

Main assumptions	Today	KEV, 2020
Total electricity demand (TWh)	112	137
Total flexible demand (TWh)	0	30
Net exports (%demand)	-11	+ 11
Solar PV (GW)	3.9	10, 15, 20
Onshore Wind (GW)	3.6	6.9
Offshore Wind (GW)	0.9	11.5
CCGT Natural gas (GW)		17.8
ETS cost (€/Tn CO2)	20	43
EPEX (%)	25	100
RES cost (€/ MWh)	0	0 (solar), 1.6 (wind)

[1] OPERA is a high detailed model of the Dutch energy system considering a detailed database for all the technological systems available, with high degree of choice in flexible technology options.
[2] EYE model has been developed to model the behaviour of flexible assets in the Dutch electricity system market, therefore it allows the modelling of high detailed flexible assets.
[3] COMPETES models the electricity market for the EU27 and UK countries. It accurately reproduces the interconnection of electricity trading as flexible solution for the e.g. Dutch market. It has been applied for simulating the NECP and TRANSFORM scenarios.

2.3.2 Case studies

In this section, several case studies are defined under the reference NECP scenario. The aim of the case studies is to evaluate the choice of various design choices on the business case for a compound (wind and battery) asset. The Borssele offshore wind farms, with a total installed capacity of 1400 MW is chosen as the reference wind farm. Based on the wind speed timeseries at the centre coordinate of this wind farm, an energy yield timeseries is obtained based on an interpolation from a sample wind farm energy yield rose plot, calculated using TNO's internal wake loss estimation tool ECN Farm Flow [21]. The energy yield timeseries is fed as input to the EYE model.

Baseline

In the baseline case, the Borssele offshore wind farms are assumed to interact directly and only with the spot market. The wind farm is not connected to a storage device and it is assumed that the revenue for the wind farm developer only comes from the day ahead spot market and the operations are subsidy-free. A battery is modelled to operate independently (without any interaction with the wind farm) and only with the spot market. The characteristics of the 1000 MWh battery in the baseline scenario are shown in Table 3 below.

Compound asset

In this case, the 1000 MWh battery and the 1400 MW Borssele offshore windfarm are modelled to act as a compound asset, as described in Section 2.1.2. The strategy chosen is threshold, with the value set at 1300 MW, which is assumed as the export cable capacity. This capacity is chosen to emulate a scenario where the installed capacity of the wind farm exceeds the export capacity (overplanting). Overplanting is beneficial for the utilization of the export cable, but leads to an increase in curtailment if the wind farm produces more than 1300 MW. In the case of the compound asset, it is assumed that the excess power would be stored in the battery, if the fill level is not too high. Table 3 shows the characteristics of the compound asset, changes from the Baseline are highlighted in **bold**.

Table 3 Characteristics of the battery in baseline case (where the battery and the wind farm are two separate assets) and compound asset case (where the two act as a single asset)

Parameter	**Unit**	**Baseline**	**Compound asset**
Wind farm connected to battery	MW	0	**1400**
Battery capacity	MWh	1000	1000
Max charge rate	MW	100	100
Max discharge rate	MW	150	150
Initial fill level	%	50	50
Battery operational cost	MWh	40	40
Battery efficiency (roundtrip)	%	90	90
Strategy	-	-	**Threshold**
Ratio	-	-	-
Threshold	MW	-	**1300**
Forecast window length	hours	-	**24**
Simulation period	hours	8760	8760

Sensitivity analysis

A sensitivity study with changes in individual parameters is carried out to assess their contribution to the uncertainty in the model. This is done by varying individual parameters as compared to the baseline and compound asset cases, to test their effects on the business case.

Table 4 Sensitivity analysis overview following *Ceteris Paribus* approach

Parameter	**Unit**	**Sens 1**	**Sens2**	**Sens 3**	**Sens 4**	**Sens 5**
Description		No battery	Operational cost	Ratio	Lower FWL	Larger battery
Wind farm connected to battery	MW	0	1400	1400	1400	1400
Battery capacity	MWh	0	1000	1000	1000	**3000**
Max charge rate	MW	-	100	100	100	100
Max discharge rate	MW	-	150	150	150	150
Initial fill level	%	-	50	50	50	50
Battery operational cost	MWh	-	**10**	10	10	10
Battery efficiency (roundtrip)	%	-	90	90	90	90
Strategy	-		Threshold	**Ratio**	Threshold	Threshold
Ratio	-	-		**0.0714**	-	-
Threshold	MW	-	1300	-	1300	1300
Forecast window length	hours	-	24	24	**16**	24
Simulation period	hours		8760	8760	8760	8760

Sensitivity 1:

The reference for the first sensitivity is the baseline case, where the battery and wind farm operate individually with the market, but are disconnected from each other. In comparison, under this sensitivity, the battery is not modelled at all, while the wind farm remains as per the baseline case. The aim of this sensitivity is to evaluate the impact of including a flexible asset such as a battery within the modelling setup.

Sensitivity 2:

In the second sensitivity, the battery operational cost is reduced from 40 €/MWh to 10 €/MWh. This is expected to provide generate more buy-sell pairs in the interaction of the battery with the market.

Sensitivity 3:

In the third sensitivity, the strategy is changed from threshold to ratio, and the ratio is set to 0.0714, which translates to 100 MW at full capacity. Intuitively, for the same value (in MW), the ratio strategy is expected to charge the battery faster, as when the wind speed is below rated, the battery would still keep being charged, which is not the case in the threshold strategy.

Sensitivity 4:

In this sensitivity, the battery forecast window is changed to 16h, 48h and 168h. This is to allow for the battery to make better decisions in creating buy-sell pairs in its interactions with the market.

Sensitivity 5:

In the final sensitivity, the battery capacity is assumed to be thrice that of the baseline case. Although this will result in higher capital expenses, this sensitivity will give insight into the influence of battery capacity on the business case for the compound asset.

3 Results

3.1 Power market representation by 2030 and how much flexibility will be required to integrate offshore wind energy

The modelling results simulate the clearing prices at hourly frequency, for the 2030 year. Here, it is presented as the price duration curve and the energy mix of supply and demand is represented with Sankey diagrams[4], executed in R software. The market size analysis and the value of the renewables are given in a dash-board, including the offshore wind utilization, to provide insights of the curtailment needs other type of contracts on top of the day-ahead power market bidding. The RES value (offshore and onshore wind and solar) is estimated as:

$$RES\ Value = \frac{\sum(clearing\ price\ *\ generation)}{\sum generation}$$

Note that additional PPA or bilateral contracts are not explicitly modelled yet in the current version of the EYE model. Having said that, to replicate what happens under more realistic conditions, in certain scenarios the “production and consumption” of energy in PPA’s is taken into account by reducing the overall capacity of energy generating assets and electricity demand in the market.

As simulated in the EYE model flexible assets have a large share as price setting technology, as well as the gas assets, since those technologies when renewable generation is not available, they continue bidding in the power market, directly dependent on the EU-ETS CO2 prices and gas price. Both renewable capacity and flexibility capacity to supply flexible demand play a main role. That means, although wind and solar sources influences as decreasing electricity prices, the flexibility assets make the system more expensive. The overall trend is a slight decrease in the average prices with respect of 2019-prices (43 €/MWh). The utilization of offshore wind is 100% in this scenario, and the value of the different RES are the following: 40 €/MWh for offshore wind, 35 €/MWh for onshore wind and 36 €/MWh for solar (**Figure 5**, **Figure 6**, **Figure 7**).

Two additional simulations considering that i) there is no flexible capacity and the ii) flexible capacity of the electrolyser is doubled from 30 TWh to 40 TWh, show that wind utilization drastically decreases when no flexibility is simulated (up to 55%) and remains 100% in the doubling flexibility. That means for a large scale renewable deployment the flexible asset capacity need also to increase for a full RES utilization. In total around 33% of the total RES production is curtailed in the No flex sensitivity case. This highlights the importance and the need of a flexible demand when RES supply will increase in the next decades.

Maximum flexible capacity is 8.54 TW in the reference case and when 15.05 TW doubling the flexibility, while the total flexible demand is 30.32 TWh/yr in the reference and 39.03 TWh/yr in the doubling case. This shows that a double flexible capacity installed does not mean a doubling of flexible demand, due to the fact that the installed capacities of energy generation assets (including RES) does not change.

Onshore and offshore wind generation and share between the supply to electricity and to flexibility demand remains unchanged with the variation of flexible capacity

[4] https://www.r-graph-gallery.com/sankey-diagram.html

installed. Whereas the wind generation is lower in the scenario with no flex assets, this is due to curtailment and it is illustrated in **Figure 5**. The total production for offshore and onshore wind decreases in the No flex scenario (from 49 TWh/yr to 27 TWh/yr for offshore wind and from 15 TWh/yr to 9 TWh/yr for the onshore wind generation). On the other hand, solar supply does not change because as its marginal cost is 0 €/MWh, it always enters first in the merit order.

In the Double flex scenario, the biomass production doubled and the gas production also increases by 5 TWh/yr compared to both Baseline 2030 and No flex scenario. As the total demand has increased, gas and biomass assets, with high marginal costs, are needed to fulfil the new flexible demand. This leads to higher prices, for both flexible demand and average clearing prices. Same behaviour is observed for batteries, which are independent assets, not connected to the renewable assets, they are activated only when flexible demand is non-zero.

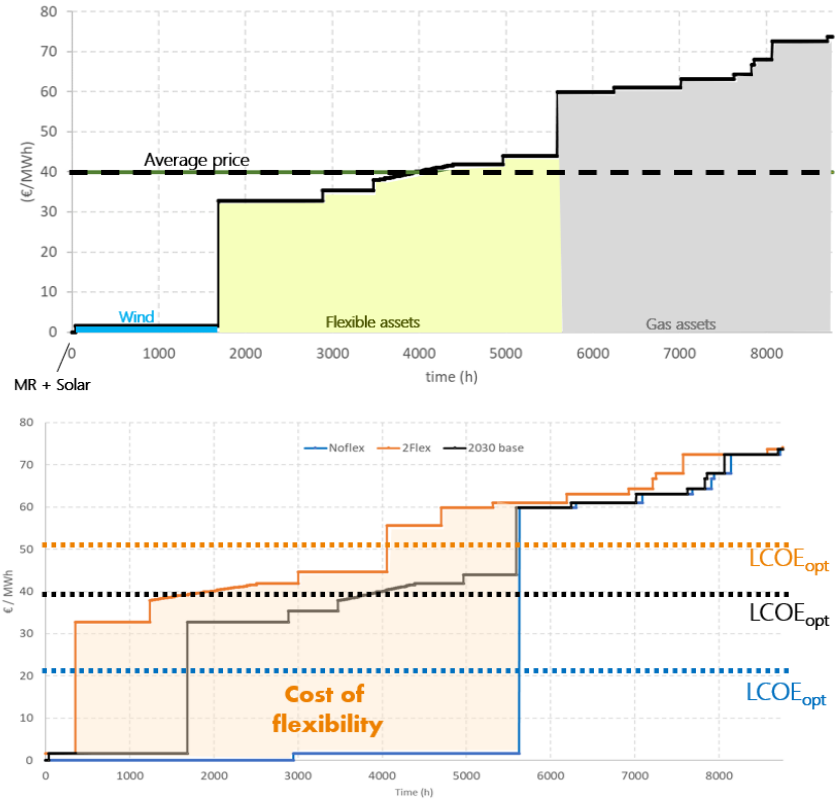

Figure 5 (top) price duration curve and technologies setting the price following KEV 2020, as a base case, including 30 TWh of flexible demand. (Bottom) sensitivity analysis of different price duration curves with different flexible capacities (orange doubling flexible demand to 40 TWh, blue no flexible demand under 2030 conditions and black, the base case).

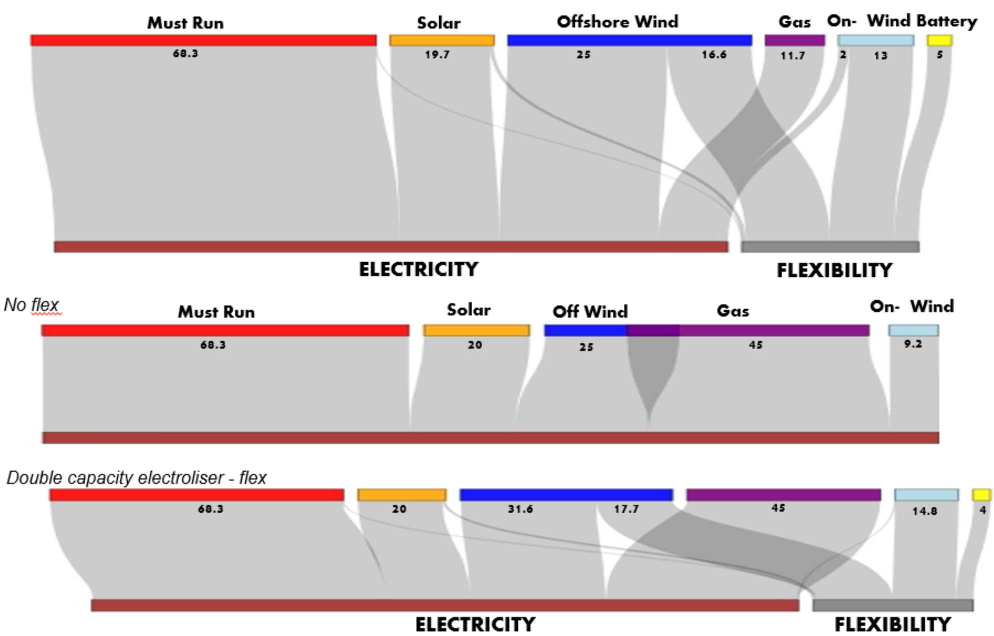

Figure 6 Sankey diagrams representing the supply and demand for 2030 power market behaviour under different flexible demand requirements in the system (top) following 2030 climate agreement estimates of 30 TWh flexible demand, (centre) with no flexible demand and (bottom) increasing flexible demand to 40 TWh.

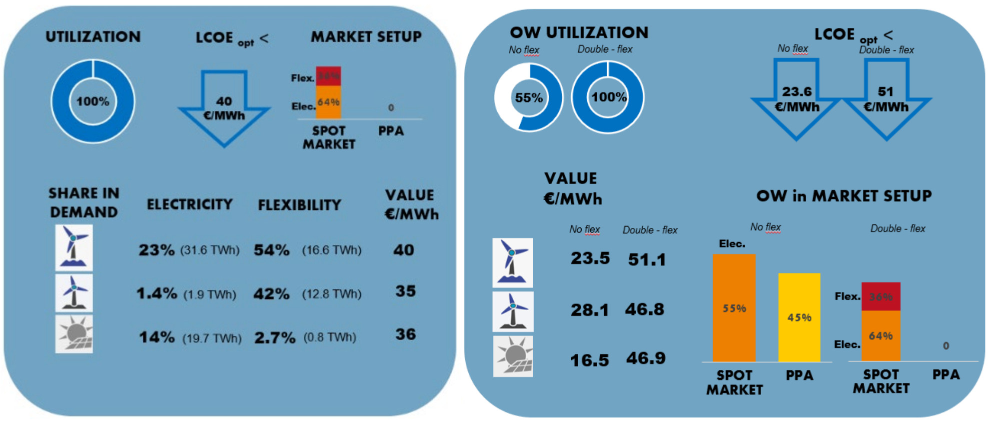

Figure 7 Dashboard summarising power market features under different flexible demand requirements in the system (left) following 2030 climate agreement considering 30 TWh flexible demand, (right) with no flexible demand (no flex) and increasing flexible demand to 40 TWh (double flex).

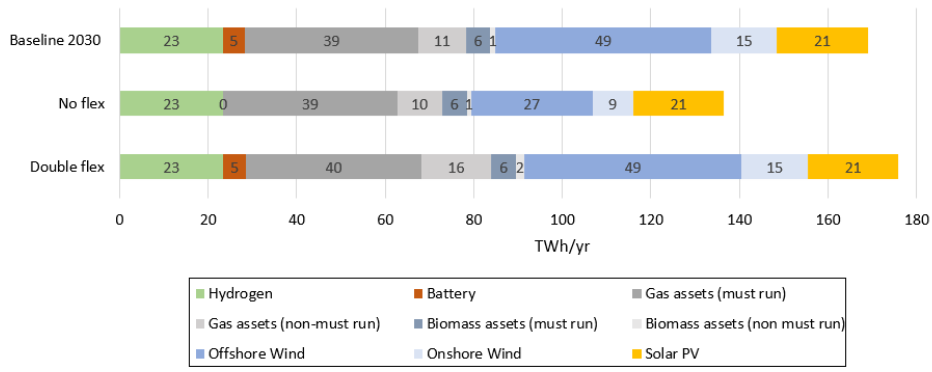

Figure 8 Electricity generation by different assets for the NECP 2030, considering no flexibility demand and doubling the flexibility demand (TWh/yr).

It is shown that the grow of new flexibility from demand response, storage and RES generation are enablers to shrink the role of conventional generation plants as flexibility providers. However, as shown in the figures below, there is still a need for additional flexibility capacity to reduce conventional sources and to maximize the value of the wind at multi/day, multi week frequency and at extreme weather events.

The figure 9 (centre) shows the correlation between the variability of the offshore wind with respect to the price duration curve and the type of technologies setting the price. As expected, while the wind is the setting price technology for the first 1800h, the offshore wind generation is higher, with low variability being able to covering both the electricity and flexible demand. Between 1800 and 5500 hours, as described above, it shows that the flexible assets are setting the price. During those hours, the wind generation is still large but the variability is higher as well, indicating that there are peaks and offpeaks.

The flexible and electricity demand is supplied by a combination of conventional and RES sources since the latest are not enough to cover baseload. This is also an indication that additional flexible options would be needed to shift the peaks of renewable to offpeaks moments, reduce volatility and therefore increase baseload. From 5500 hours to 8760 hours, the effect of volatility and dependency of gas is more pronounced. The wind generation is lower than the rest of the hours and the demand is supplied mainly by gas. Here, additional flexible sources such as the LDES could provide additional services, increasing baseload generation reducing the conventional supply.

The Figure 9 (bottom), indicates the intermittency of the wind, when there are consecutive hours with a certain generation. This is translated in the number of storage hours necessary to shift and store during hours of peaks and discharge during offpeaks. In the modelling case, it is also considered the size and utilization of the battery (section 3.2) and how the wind business case in connection with the battery could have a more profitable business (3.3). That is, while the generation is very low/high, how many consecutive hours this effect persists. While in the 1-1800 hours the wind covers the entire supply and 1800-5500 h is to supply the flexible demand, > 5500 to replace conventional sources, the range of number of hours of storage based on the flexibility estimated by 2030 is between 4 and 25 hours.

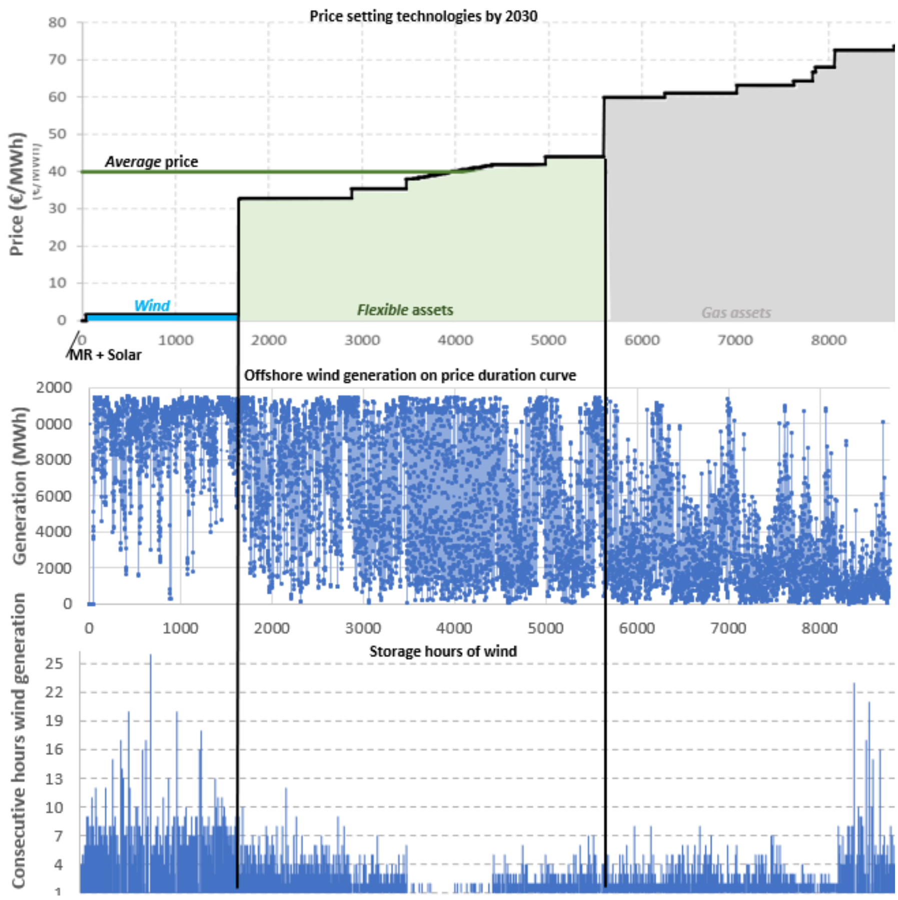

Figure 9 (top) price duration curve and technologies setting the price under the TNO scenario following KEV 2020. (centre) offshore wind generation sorted with respect to the price duration curve. (bottom) number of consecutive hours of wind generation and storage necessary hours to shift in time the discharge into the power market to increase baseload generation

3.2 Optimum battery design to improve wind business case under 2030 market conditions and grid infrastructure.

The optimization problem described in Section 2.2 was used to find the optimal charging and discharging power of the battery with a fixed capacity of 1 GWh, as considered in Section 0. This optimization yielded an optimal charging and discharging power and corresponding storage hours, as shown in Table 6. Additionally, the time shift introduced by battery of the optimized case also improves the utilization rate of the export cable, reduces curtailment and increases expected revenue compared to the base case without battery. This can be seen from Table 6 below and graphically in the duration curve of **Figure 10**.

Table 5 Optimum design characteristics of the battery.

	Optimized case
Optimal charging power [MW]	100
Optimal discharging power [MW]	570
Storage hours (charging) [h]	10
Storage hours (discharging) [h]	1.7

Table 6 Basic descriptive statistics for the base and optimized battery system, with a battery charging and discharging power of 100 MW and 570 MW, respectively.

	Base case	Optimized case
Peak generation [MW]	1400	1300
Total aggregated generation [GWh]	5336	5336
Cumulative generation curtailed [GWh]	161	113
Energy curtailed [%]	3.02%	2.12%
Total generation to grid [GWh]	5175	5222
Utilization rate of grid connection [%]	45.44%	45.86%
Grid infrastructure [MW]	1300	1300
Total revenue [M€]	353.2	357.4

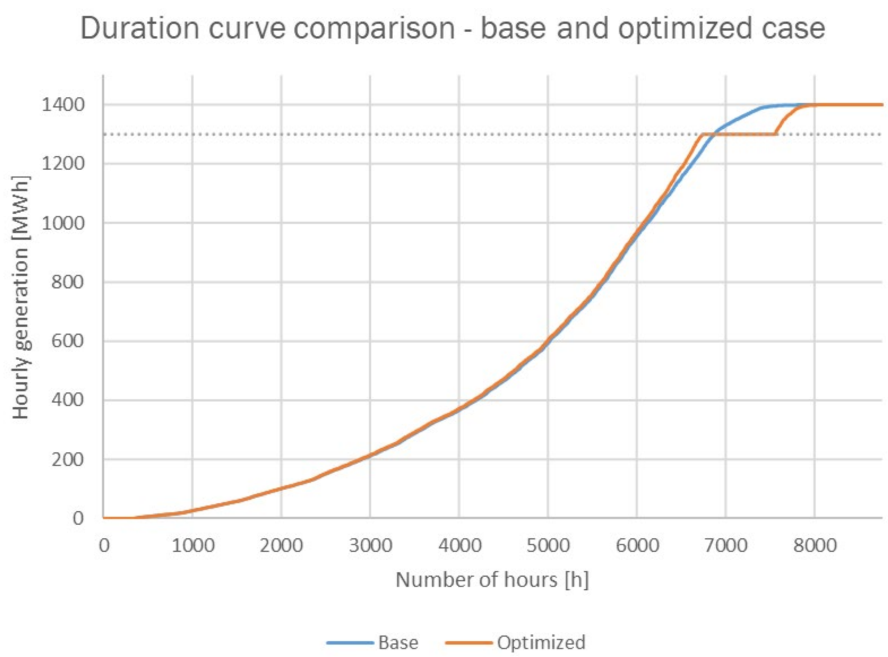

Figure 10: Duration curve comparison between the base case without battery, and optimized case including a battery.

This comparison shows the impact of a battery with a fixed capacity of 1 GWh, which is 0.02% of the annual generation (5222 GWh), where the battery leads to a 30% reduction in curtailment. In the base case, there are a total of 1886 hours generation above 1300 MW, which reduces to 1201 hours in the optimized case.

As also shown in section 3.1, from power system level, there is a need for additional flexibility in the form of storage from ~5500 hours onwards (Figure 9, top). This business case, simulating Borssele wind farm connected with a battery, shows that the battery improves the total generation to the grid, by reducing curtailment from ~6000h onwards. During those hours, the battery stores the wind generation, time-shifting the moment when some of the generated power is discharged to the power market. On average, the generated wind is stored for approximately 7 hours before discharging to the market.

This curtailment reduction combined with the time-shifting potential introduced by the battery also leads to an increase in the expected revenue. The increase in revenue is about 4 M€ with respect to the base case. This means that, assuming a project lifetime of 25-30 years, there is an allowable margin for the battery cost of roughly 100 M€. Assuming the 1 GWh battery capacity, this translates to an equivalent cost of 100 €/kWh, close to the expected threshold for price competitive battery storage, as also stated in [22].

3.3 Hybrid power plant (wind-battery) behavior in the power market

For the reference scenario and the scenario with wind-battery compound assets, the table below shows results over a simulation period of one year. Following are definitions of the key performance indicators of the simulated cases:

- ‘Average fill level’ is the mean of the individual fill levels of the battery over the simulation period
- ‘Average clearing price’ is the mean of individual prices output by the simulator during the simulation period
- ‘Cumulative offshore wind supply to battery’ is the sum of energy supplied from the offshore wind farm to the battery over the simulation period.
- ‘Cumulative offshore wind supply to market’ is the sum of energy supplied from the offshore wind farm to the battery over the simulation period
- ’Cumulative battery purchase from market’ is the sum of energy discharged from the battery to the market over the simulation period
- ‘Cumulative battery supply to market’ is the sum of energy charged by the battery from the market over the simulation period
- ‘Total offshore wind revenue’ is obtained by multiplying at each timestep the clearing price and the offshore wind supply to the market
- ‘Total battery revenue’ is obtained by multiplying at each timestep the clearing price and the battery supply to the market
- ‘Total battery cost’ is obtained by multiplying at each timestep the clearing price and the market supply to the battery
- During the simulation, a build-up in the fill level of the battery could occur. ‘Value of stored power in the battery’ is obtained by multiplying the difference in the fill level at the start and end of the simulation by the average clearing price over the simulation period.
- Finally, the net revenue of the wind-battery compound asset is calculated as the sum of ’Total offshore wind revenue’, ‘Total battery revenue’, ‘Value of stored power in the battery’ minus ‘Total battery cost’.

Table 7 Results for reference case and the sensitivities on the compound assets bidding in the power market

Parameter	Unit	Baseline	Sens 1	Compound asset	Sens 2	Sens 3	Sens 4	Sens 5
Description		Battery separate	No battery	Battery connected	Oper. cost	Ratio	FWL =16h	Larger battery
Average fill level	%	41.58	50	52.17	49.07	64.27	55.51	48.88
Average clearing price	€/MWh	55.38	55.4	55.4	55.41	55.4	55.39	55.4
Cum. offshore wind supply to market	MWh	5318651	5313752	5268181	5241463	5193604	5263262	5241721
Cum. offshore wind supply to battery	MWh	0	0	49553	72678	121622	50590	78196
Cum. battery purchase from market	MWh	88500	0	63329	93652	34134	60304	81809
Cum. battery supply to market	MWh	88638	0	112654	166058	155472	110600	159106
Total offshore wind revenue	M€	261.77	261.98	259.89	258.85	256.01	259.93	259.33
Total battery revenue	M€	6.20	0	7.71	11.2	10.6	7.51	11.08
Total battery cost	M€	0.73	0	0.64	2.13	0.39	0.67	0.61
Battery utilisation	%	16.51	0	20.59	29.42	48.97	19.93	29.19
Value of stored power in battery	M€	0.00	0	0.012	0.015	0.015	0.016	0.049
Net profit compound wind-battery asset	M€	266.96	261.98	266.98	267.94	266.29	266.80	269.85

In the baseline case, where the battery and wind farm are not connected to each other, the net profit for the compound asset is 266.96 M€. There is no supply from the offshore wind farm to the battery, and the battery only charges and discharges from the market. In the first sensitivity, the battery is removed from the simulation, and only the wind farm's revenue is calculated, which amounts to 261.98 M€.

In the compound asset case, where the battery is connected to the offshore wind farm and stores energy using the threshold strategy, there is naturally an increase in offshore wind supply to the battery. This however doesn't really translate to a higher net profit for the system, as the additional revenue from the battery does not compensate for the revenue from the wind farm in the baseline case.

In the second sensitivity, when the operational cost of the battery is lowered to 10 €/MWh, there is an increase of ~1M€ net profit, which can be attributed to a larger number of buy-sell pairs being generated during the simulation. This is also seen in the increase in cumulative energy traded between the battery and the market.

In the third sensitivity, the application of strategy ratio decreases the net profit to 266.29 M€. As expected, there is an increase in offshore wind energy stored in the battery. However, this also results in a lower amount of energy purchased by the battery from the market at low and competitive prices, which may negatively affect the net profit.

The decrease of forecast window length has a very small impact on the net profit, which can be attributed to the reduction in number of hours for which the battery has the knowledge of market prices, thereby hindering it in creating ideal buy-sell pairs.

Finally, when the battery capacity is increased by a factor of three, the net profits increase, as there is a possibility for the battery to store larger amounts of wind energy, and trade it in the market place.

The reduction of the forecast window length to 16 hours seems to reduce the overall profits of the wind-battery compound asset. With a reduced forecast window length, there is a smaller chance for the battery to make better choices in terms of buying and selling power from the market, which results in reduced profits.

Overall, for the present configuration of the wind battery compound asset, the operational cost and forecast window length have a small effect on the net profit of the system. The implementation of the model has been tested and works correctly, but more research is needed to understand the behaviour of the strategy ‘ratio’, while it is clear that increasing the capacity of the battery will lead to higher net profits.

4 Conclusions and further research

The emergence of hybrid power plants as one single asset bidding in the power market have required implementation of new methodologies. Research is required both for model implementation and adaptation and to evaluate their impact on system perspective and from the wind business case.

This study consists of modelling the future power market behaviour by 2030 following the targets of the Climate Agreement to evaluate the flexibility requirements and the role of connecting the wind with battery at large scale, estimating the hours of storage would be required. A reference case, where the battery and wind farm are unconnected is compared with a hybrid asset, where the battery stores the power from the wind farm as an smart system.

Firstly, mathematical optimization is performed to estimate the optimum design of the battery in connection with a wind (1.4 GW capacity, as Borselle wind farm of case study) considering as an objective function the maximization of the profit and the utilization of the battery. Such a battery can already mitigate a significant amount of curtailment, which is all power above 1300 MW in this case. This curtailment reduction combined with the time-shifting potential introduced by the battery also leads to an increase in the expected revenue. The increase in revenue is about 4 M€ with respect to the base case. This means that, assuming a project lifetime of 25-30 years, there is an allowable margin for the battery cost of roughly 100 M€. Assuming the 1 GWh battery capacity, this translates to an equivalent cost of 100 €/kWh, close to the expected threshold for price competitive battery storage.

Finally, the optimum compound system (battery and wind connected as a single asset) bids into the power market and it is investigated the optimum bidding strategy of charge and discharge. Preliminary results from the case study and sensitivities show that the decreasing the operational cost and increasing forecast window length have a small effect on increasing the net profit of the system. More research is needed to understand the optimal conditions to implement the strategy 'ratio', while increasing the capacity of the battery will lead to higher net profits

Further work is will be done by elaborating the strategy and optimizing the configurations of the battery in connection with wind. In addition to that, further model developments are carrying out to model hybrid power plant as one single actor in the power market, considering other renewable, storage and conversion technologies, such as floating solar, hydrogen conversion and technology-specific batteries.

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A Nomenclature

An overview of the symbols used in the optimization problem of Section 2.2 are presented in Table A1 below.

Table A1: Nomenclature

Parameter	Description
$\mathcal{C}_{bat}$	Battery cost [€]
C_{eq}	Equivalent capital expenditure [€]
$\mathcal{C}_t$	Cost at time *t* [€]
E_{bat}	Rated battery capacity [Wh]
E_t	Current battery charge [Wh]
$E_{threshold}^{bat}$	Value beyond which wind farm power is stored in battery [MWh]
F_t^{bat}	Battery fill level [Wh]
L_{bat}	Expected battery lifetime [years]
P_{ch}	Maximum battery charging power [W]
P_{curt}	Curtailed power [W]
P_{dis}	Maximum battery discharging power [W]
P_t^{bat}	Energy from WF stored in battery [MWh]
P_t^{market}	Energy from WF for trading in the market [MWh]
P_t^{WF}	Wind farm power [W]
$P_t^{b,in}$	Battery charging power [W]
$P_t^{b,out}$	Battery discharging power [W]
P_t^e	Exported power [W]
$\mathcal{P}_t$	Profit at time *t* [€]
$\mathcal{R}_t$	Revenue at time *t* [€]
SOC_{init}	Initial battery state-of-charge [-]
Δt	Timestep [h]
η_{ch}	Battery charging efficiency [-]
η_{dis}	Battery discharging efficiency [-]
λ_{LCOE}	Levelized cost of the wind farm electricity [€/Wh]
$\lambda_{b,ch}$	Battery charging cost [€/Wh]
$\lambda_{b,dis}$	Battery discharging cost [€/Wh]
$\lambda_{b,unit}$	Battery unit cost [€/Wh]
λ_t	Market price [€/Wh]
μ_{curt}	Penalty factor (cost) of curtailed power [€/Wh]