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Iori, J.; Zaaijer, M B; Kreeft, J.; von Terzi, D.A.; Watson, S.J.

DOI
10.1088/1742-6596/3025/1/012023

Publication date
2025

Document Version
Final published version

Citation (APA)
Iori, J., Zaaijer, M. B., Kreeft, J., von Terzi, D. A., & Watson, S. J. (2025). *Reliable operation of wind-storage systems for baseload power production*. Paper presented at WindEurope Annual Event 2025, Copenhagen, Denmark. https://doi.org/10.1088/1742-6596/3025/1/012023

Journal of Physics: Conference Series

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To cite this article: Jenna Iori *et al* 2025 *J. Phys.: Conf. Ser.* **3025** 012023

Reliable operation of wind-storage systems for baseload power production

Jenna Iori[1], Michiel Zaaijer[1], Jasper Kreeft[2], Dominic von Terzi[1], Simon Watson[1]

[1]Faculty of Aerospace Engineering,TU Delft, Delft, The Netherlands.
[2]Shell Global Solutions International BV, The Hague, The Netherlands

E-mail: j.iori@tudelft.nl

Abstract. As the penetration of renewable energy increases in the generation mix, the problem of power dispatchability becomes more critical. The co-location of storage systems with wind energy is a promising solution to shift power delivery from periods of high wind resource availability to periods of high electricity demand. Producing baseload power from wind farms all or most of the time is an example of such dispatchability. In this work, we present an optimization-based dispatch strategy to produce baseload power. At every time step, an optimization problem is solved to decide the storage operation, maximize revenues on the electricity market and reach a given reliability target. In order to reduce the impact of forecast uncertainties on the reliability of the power delivery, a robust formulation of the dispatch optimization is used, based on a pessimistic version of the forecast. The proposed method is evaluated for 18 offshore sites with a 100 MW wind farm and storage system, for one year of operation. By using a robust dispatch strategy, the reliability increases by up to 0.9 points, with a minor impact on revenues (+2% on average), compared to the reference dispatch strategy using a regular forecast. Our study demonstrates the feasibility of providing a reliable baseload power from wind energy in the presence of forecast uncertainty.

1 Introduction

The lack of dispatchability of wind energy is a significant challenge for grid stability and reliability of supply, in scenarios of high penetration of renewable energy. The co-location of wind farms with energy storage provides a possible solution. This type of system is effective in mitigating the variability of wind power [1, 2] and compensating forecast error when aiming to produce scheduled or reference power [3, 4, 5]. A relevant use-case for increasing the dispatchability of wind power is the production of baseload power where minimum power is produced most or all of the time [6, 7]. A baseload hybrid power plant pilot, called the Baseload Power Hub, is currently under construction at the Hollandse Kust Noord wind farm as part of the CrossWind innovation program [8]. This system is designed to provide at least 20% of the average power production of a wind turbine 99% of the time and will demonstrate the technical feasibility of this type of power plant.

The relevance of a baseload wind-storage power plant lies in its reliability, i.e. its ability to provide a minimum load consistently regardless of variations of the wind resource. Forecast uncertainties increase the risk of not achieving a steady and sufficient power supply. As such, the dispatch schedule of the storage system is critical. Dispatch methods based on *if-then* rules can be used to mitigate the variability of the wind power [4, 9]. More advanced strategies based on optimization have been developed to take

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full advantage of forecast information for bidding in the electricity market [10, 11, 5]. However, these approaches do not address the question of reliability considering forecast uncertainties.

In this work, we explore the use of a *robust* approach for the dispatch optimization strategy of the storage system, inspired from the field of robust optimization. A pessimistic version of the power forecast is used as an input for the dispatch optimization, underestimating the expected power production. This approach encourages a conservative operation of the storage system and as such is promising for increasing the reliability of the power delivery. The present paper presents the robust dispatch optimization, and addresses the following research question: To what extent does a robust approach improve the reliability of baseload production for wind-storage systems?

The rest of the paper is divided as follows: The next section reports the models used to represent the storage system, wind power production and forecast. The rest of the section presents the dispatch optimization and its robust version. The numerical experiments designed to answer the research question are reported in Section 3, and the corresponding results shown in Section 4. Finally, Section 5 and 6 provides suggestions for future work and conclusions for the study.

2 Methodology

2.1 Storage system model

The storage system is described with its macro-parameters: power capacity $\bar{P}$, energy capacity $\bar{E}$ and round-trip efficiency η. The operation of the storage system is described with the power P_i and energy E_i at each time step i. We use the convention that the power is positive in discharge and negative in charge. The following model is used to link the storage power in charge or discharge to its energy level, over a given number of time steps n and with a time step Δt:

$$E_{i+1} - E_i = \begin{cases} -\Delta t P_i & \text{if } P_i \geq 0, \\ -\dfrac{\Delta t}{\eta} P_i & \text{else,} \end{cases} \qquad i = 0, ..., n-1, \tag{1}$$

$$-\bar{P} \leq P_i \leq \bar{P} \qquad i = 0, .., n-1,, \tag{2}$$

$$0 \leq E_i \leq \bar{E} \qquad i = 0, .., n. \tag{3}$$

2.2 Wind farm model

A simple wind farm model is used to describe the dependency of the power production on the wind speed u and wind direction θ, represented by the functions

$$f_{\mathrm{WF}}(u,\theta) = n_{\mathrm{WT}} \cdot \min(P_{\mathrm{R}}, (1 - f_{\mathrm{WL}}(\theta)) f_{\mathrm{WT}}(u)), \tag{4}$$

$$f_{\mathrm{WT}}(u) = \begin{cases} \dfrac{1}{2}\rho C_P A u^3 & \text{if } u_{\mathrm{in}} \leq u \leq u_{\mathrm{out}}, \\ 0 & \text{else.} \end{cases} \tag{5}$$

where n_{WT} is the number of wind turbines, P_{R} the turbine rated power, ρ the air density, C_P the power coefficient, u_{in} and u_{out} the cut-in and cut-out wind speeds, A the rotor area, and $f_{\mathrm{WL}}(\theta)$ a wake loss term with a periodicity of 60^o and a maximum of 0.25. The model is illustrated in Figure 1. It was developed to approximate the IEA Wind 740-10-MW Reference Offshore Wind Plant with a regular layout [12].

2.3 Forecast

The power forecast is generated based on numerical weather prediction forecast data from ECMWF's Integrated Forecast System. A wind speed forecast is available every 12 hours. For every forecast issue, the forecast is retrieved with a varying resolution, between 1 hour (for lead-times up to 12 h), 2 hours (for lead-time between 12 and 24 h) and 3 hours (for lead-time above 24 h). A cubic interpolation is used as necessary to provide a one-hour resolution for the entire range of lead times. Observation data are obtained from ERA5 [13]. From the data of the wind speed and wind direction (forecast and observation), the corresponding power production from the wind farm is obtained using Equation 4. Let $\hat{u}^{\mathrm{WF}}_{i+j|j}$ and $\hat{\theta}^{\mathrm{WF}}_{i+j|j}$ be the wind speed and direction forecast issued at time j for a lead time i. The corresponding power forecast $\hat{P}^{\mathrm{WF}}_{i+j|j}$ is calculated as

$$\hat{P}^{\mathrm{WF}}_{j+i|j} = f_{\mathrm{WF}}(\hat{u}_{j+i|j}, \hat{\theta}_{j+i|j}). \tag{6}$$

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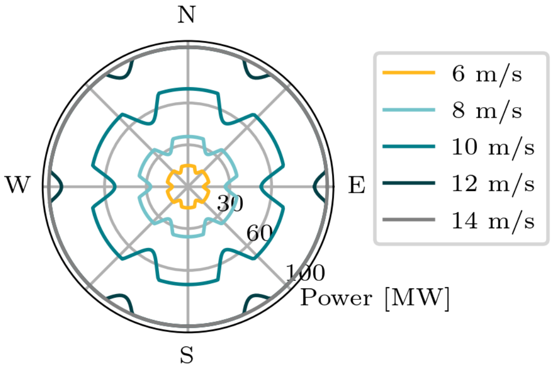

Figure 1: Wind farm power production as a function of wind speed and wind direction.

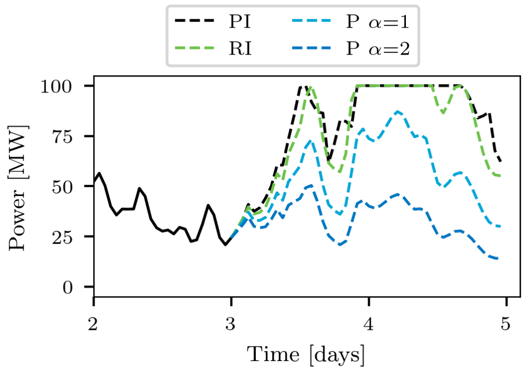

Figure 2: Example of perfect information (PI), real information (RI), and pessimistic (P) forecasts.

2.4 Dispatch optimization

The operation of the storage system is decided using an online optimization, where the results of an optimization problem solved at each time step give the power when charging or discharging the storage system. The objective of the optimization is to maximize revenues over a given time window corresponding to the maximum power forecast lead time. A simple revenue model is used, where a varying electricty price, noted $\boldsymbol{\lambda}$, is associated with the power delivered to the grid. Market bidding mechanisms are not modelled in this work. Furthermore, the dispatch optimization aims at satisfying a minimum baseload power production P_{BL} with a given target reliability $\tilde{r}$.

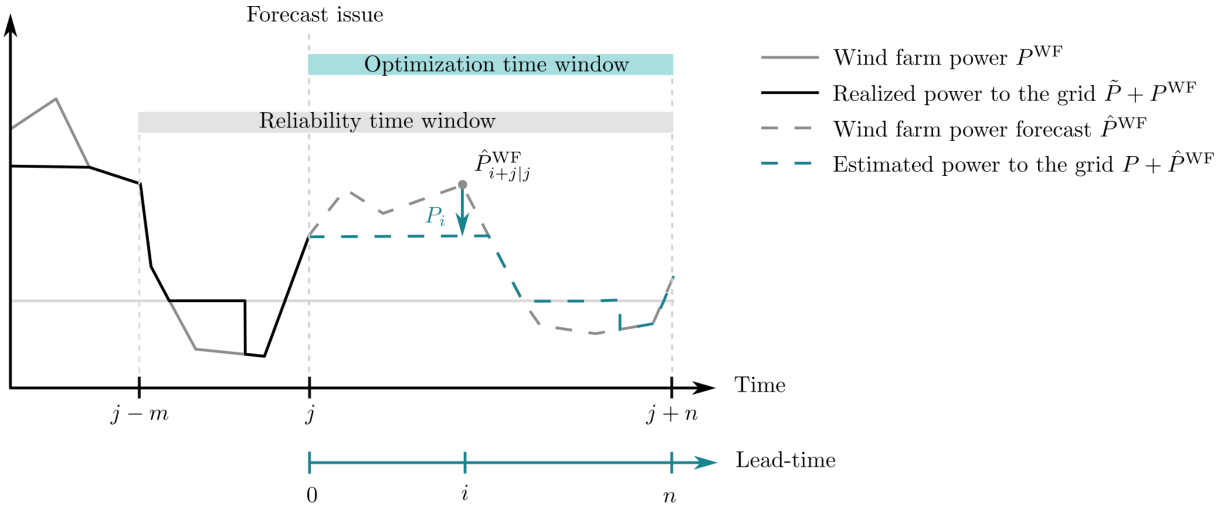

Figure 3: Schematic representation of the dispatch optimization. The time scale related to the forecast and the optimization problem is shown in blue and indexed by i. Real-time is indexed by j.

Figure 3 illustrates the online optimization for a given time step j. A forecast is issued at this time step and gives an estimation of the power produced by the wind farm over the next n time steps. The solution of the optimization problem gives the expected storage operation schedule $P_i,\ i = 0, ..n - 1$. Finally, the storage system is operated for one time step following the optimum. The realized storage power and energy level are denoted by $\tilde{P}_j$ and $\tilde{E}_j$. Here, two different indexing are used. The indexing related to real-time is denoted by j, whereas the index i is used to refer to the forecast lead-time and the optimization time window.

The reliability of the baseload power production is the proportion of time where the power delivered to the grid is equal or above the baseload level P_{BL}. The reliability should reach its target value when measured over months or years. However, this long time window is difficult to capture within the online optimization, due to the short time scale of the forecast. As a solution, a short-term reliability measure is used within the dispatch optimization, calculated over n time steps ahead of the current time and m time steps before. This time window is illustrated in Figure 3. By considering previous time steps, this metric can better approximate the reliability calculated over months or years. In order to describe the metric in mathematical terms, binary variables denoted by $\boldsymbol{z}$ are used to represent if the baseload power is delivered or not at each time step. Considering h the number of times over the past m time steps where the baseload power is not achieved, the short-term reliability r_j for a given time step j is calculated as

$$r_j(\boldsymbol{z}, h) = \frac{1}{m+n}\left(h + \sum_{i=0}^{n-1} z_i\right), \quad \text{where } z_i = \begin{cases} 1 & \text{if } P_i + \hat{P}^{\mathrm{WF}}_{j+i|j} \geq P_{\mathrm{BL}}, \\ 0 & \text{otherwise}, \end{cases} \tag{7}$$

The optimization problem is formulated as a mixed-integer linear program. The corresponding mathematical formulation is reported in Equations (8)-(14), for a given time step j. The design variables are the storage energy level and power over the forecasting time window $\boldsymbol{E}, \boldsymbol{P}$, as well as binary variables $\boldsymbol{z}$ and a penalty term $p \in \mathrm{R}^+$ associated with the reliability constraint. Equation (9) enforces upper and lower bounds on the power delivered to the grid. The binary variable z_i dictates if the lower bound is zero or the baseload power P_{BL} for lead-time i. Equation (10) constrains the reliability r_j to be above the target reliability $\tilde{r}$. Here, the penalty term p serves as a slack variable to ensure that the feasible set for the problem is not empty. Equation (11) ensures that the initial energy level within the optimization problem corresponds to the realized energy level at the considered time step j. Equations (12)-(13) represent the storage system model, in a relaxed form. This choice of formulation reduces the number of binary design variables and in turn the computational burden of solving the problem. Finally, the bounds on $\boldsymbol{P}$ and $\boldsymbol{E}$ are enforced through the last constraint.

$$\begin{aligned}
\underset{p\in\mathrm{R}^+, \boldsymbol{z}\in\{0,1\}^n, \boldsymbol{E}\in\mathrm{R}^{n+1}, \boldsymbol{P}\in\mathrm{R}^n}{\text{maximize}} \quad & \sum_{i=0}^{n} \lambda_{i+j} P_i - \mu p + \beta E_n && && (8)\\
\text{subject to} \quad & P_{\mathrm{BL}} z_i \leq P_i + \hat{P}^{\mathrm{WF}}_{j+i|j} \leq P_{\max} && i = 0,..,n-1 && (9)\\
& r_j(\boldsymbol{z}, h) \geq (\tilde{r} - p) && && (10)\\
& E_0 = \tilde{E}_j && && (11)\\
& E_{i+1} - E_i \leq -\Delta t P_i && i = 0,..,n-1 && (12)\\
& E_{i+1} - E_i \leq -\frac{\Delta t}{\eta} P_i && i = 0,..,n-1 && (13)\\
& \text{Eq. (2-3)} && && (14)
\end{aligned}$$

The objective function is made up of three terms. The first term represents storage revenues, which include loss of revenues when charging, and added revenues when discharging. The second term is associated with the penalty on the reliability and drives the algorithm to choose a solution where the target reliability is reached and $p = 0$. The last term is added due to the relaxation of the storage model, to ensure the storage system equation holds even if $\hat{P}^{\mathrm{WF}}_{j+i|j} = P_{\max},\ i = 0, ..., n-1$. The relaxation also requires that the electricity price is positive for all time steps, $\lambda_{i+j} > 0,\ \forall i$. The factors μ and β are tuning parameters. Algorithm 1 reports how the storage dispatch is decided based on the solution of the optimization problem.

2.5 Robust formulation using pessimistic forecast

The optimization problem represented by Equations (8)-(14) is written using a deterministic approach with a point forecast $\hat{P}^{\mathrm{WF}}_{j+i|j},\ i = 0, ..., n-1$. However, due to forecast uncertainties, the actual power can be lower than the forecasted value. In this situation, the constraint related to the baseload power represented by Equation (9) does not consider such uncertainties, and may lead to a lower reliability.

In order to take into account such uncertainties in the dispatch optimization problem, it is reformulated as a robust optimization using a chance-constrained approach [14], with probability $1 - \epsilon$. Considering all possible power scenarios $\boldsymbol{P}^{\xi},\ \xi \in \Xi$, the chance-constrained version of Equation (9) is

$$\mathbb{P}_{\xi\in\Xi}\left(P_{\mathrm{BL}} z_i \leq P_i + P^{\xi}_{j+i} \leq P_{\max}\right) \geq 1 - \epsilon,\ i = 0, .., n-1. \tag{15}$$

Algorithm 1 Dispatch strategy based on an online optimization

Require: $\boldsymbol{\lambda}$, $\tilde{r}$, P_{BL}, $\bar{P}$, $\bar{E}$, n, m, N
  Initialize $\tilde{E}_0$
  for $0 \leq j \leq N$ **do**
    Generate forecast $\hat{P}^{\mathrm{WF}}_{j+i|j}$ for $i = 0, ..., n-1$
    $h \leftarrow 0$
    if $j \leq m$ **then**
      $h \leftarrow \sum_{k=0}^{j-1} \tilde{z}_k$
    else if $j \geq m$ **then**
      $h \leftarrow \sum_{k=j-m}^{j-1} \tilde{z}_k$
    end if
    Solve optimization problem represented by Eqs. (8-14) and obtain the solution $\boldsymbol{E}, \boldsymbol{P}, \boldsymbol{z}$
    Operate the storage for one time step: $\tilde{P}_j \leftarrow P_0$, $\tilde{E}_{j+1} \leftarrow E_1$, $\tilde{z}_j \leftarrow z_0$
  end for

Instead of generating a representative ensemble of the set Ξ for the evaluation of the constraint, a pessimistic version of the forecast, noted $\hat{P}^{\text{WF-}}$, is generated under the assumption that it constitute a lower bound for the power scenarios with a probability $1 - \epsilon$, i.e

$$\mathbb{P}_{\xi \in \Xi}\big(\hat{P}^{\mathrm{WF-}}_{j+i|j} \leq P^{\xi}_{j+i}\big) \geq 1 - \epsilon, \;\; i = 0, .., n-1. \tag{16}$$

Using this pessimistic version of the forecast, Equation (17) is rewritten as

$$P_{\mathrm{BL}} z_i \leq P_i + \hat{P}^{\mathrm{WF-}}_{j+i|j} \leq P_{\max}, \imath = 0, .., n-1. \tag{17}$$

We note that the two equations are not equivalent when it comes to the upper bound. However, we assume that this aspect has a limited impact on the performance of the system. The robust dispatch optimization problem has the same formulation as the regular dispatch optimization problem presented before, but using a pessimistic version of the power forecast instead. In other words, solving the robust dispatch optimization problem is equivalent to solving the regular dispatch optimization problem with a pessimistic power forecast signal.

The pessimistic version of the power forecast is generated from a downgraded version of the wind speed forecast. This signal, noted $\hat{u}^{-}$, is obtained by reducing the original forecast value by a factor proportional to the standard deviation of the wind speed forecast error, σ_i, as

$$\hat{u}^{-}_{j+i|j} = (1 - \alpha \frac{\sigma_i}{u_{\mathrm{mean}}}) \hat{u}_{j+i|j}, \;\; \forall i, j, \tag{18}$$

where u_{mean} is the average wind speed over one year of observation data. The pessimistic power forecast is then calculated as

$$\hat{P}^{\mathrm{WF-}}_{j+i|j} = f_{\mathrm{WF}}(\hat{u}^{-}_{j+i|j}, \hat{\theta}_{j+i|j}). \tag{19}$$

The term α allows to adjust the level of pessimism of the forecast, and in turns the level of robustness of the optimization problem, represented by ϵ. A higher value of α means that the baseload power constraint is satisfied with a higher probability. It is however outside the scope of this work to determine the exact relationship between α and ϵ. Figure 2 illustrates two pessimistic forecasts with varying values of α.

3 Test cases

The regular dispatch optimization strategy is compared to the proposed robust approach. In practice, the dispatch optimization problem is solved using four different forecast signals: a perfect information forecast with zero forecast error, a real information forecast, and two pessimistic versions of the real information forecast with different pessimism levels ($\alpha = 1$ and $\alpha = 2$), illustrated in Figure 2. The results obtained with a perfect information forecast serve as a reference. Furthermore, the methodology is compared to a more simple approach, using a rule-based strategy illustrated in Figure 4. In this strategy the decision to charge or discharge the storage is based on the instantaneous wind power P^{WF}_j and price λ_j, only.

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It is tuned by choosing the two threshold parameters for power and price, P_{th} and λ_{th} respectively, to maximize the storage revenues and satisfy the target reliability. In all cases, price forecast is not modeled and the information on price is assumed to be perfect.

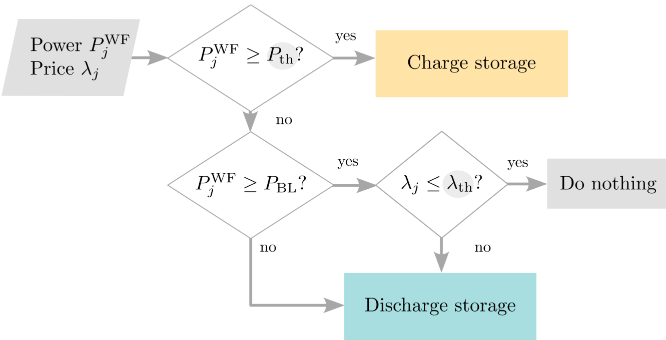

Figure 4: Logic of the rule-based operation strategy.

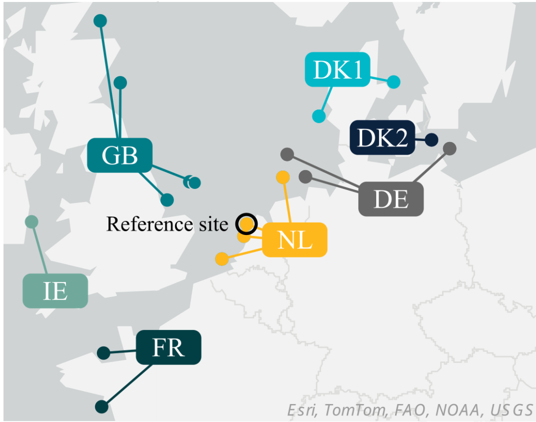

Figure 5: Site locations and associated electricity markets

Two performance metrics are used to compare the different cases: storage revenues and reliability of the baseload power production. Considering the price signal $\boldsymbol{\lambda}$ and the realized storage power $\tilde{\boldsymbol{P}}$, the storage revenues are calculated over n_T time steps as $\sum_{j=0}^{n_T-1} \lambda_j \tilde{P}_j$.

The reliability r of the baseload power production is calculated in a similar fashion as in Equation (20). The difference is that the calculation is applied to the realized storage power $\tilde{\boldsymbol{P}}$, realized wind farm power $\boldsymbol{P}^{\mathrm{WF}}$ and corresponding binary variables $\tilde{\boldsymbol{z}}$:

$$r = \frac{1}{n_T} \sum_{j=0}^{n_T-1} \tilde{z}_j, \quad \text{where } \tilde{z}_j = \begin{cases} 1 & \text{if } \tilde{P}_j + P_j^{\mathrm{WF}} \geq P_{\mathrm{BL}}, \\ 0 & \text{otherwise}, \end{cases} \tag{20}$$

To assess the performance of the proposed robust approach, we consider a 100 MW offshore wind farm in Europe, required to satisfy a baseload level $P_{\mathrm{BL}} = 10$ MW, with a reliability target of 99%. We use $n_{\mathrm{WT}} = 10$, $C_P = 0.45$ and a rotor radius of 90 m. Figure 5 shows the different locations considered, and the reference site. The price signal $\boldsymbol{\lambda}$ corresponds to the day-ahead electricity price from ENTSO-E [15]. All data are extracted for the year 2019, and the storage operation is simulated for approximately one year, with a time-step of one hour and $n = 8600$. A 48-hour forecast window is considered for the dispatch optimization strategy. Since the dimension of the storage required to satisfy the baseload constraint may vary between sites, different storage sizes are used, decided using the sizing method described in [6]. We assume a round-trip efficiency of 85%, corresponding to the efficiency of battery systems. Finally, the reliability window includes one week of operation before the current time step with $m = 168$. The optimization problem is solved using MOSEK [16], with $\mu = (n+m)P_{\mathrm{BL}}\max_i(\lambda_{j+i})$ and $\beta = 10^{-6}$.

4 Results

4.1 Reference site

A comparison is first run for the reference site, represented in Figure 5. For this site, the storage has a power capacity of 10 MW and an energy capacity of 538 MWh. Figure 6 and 7 reports the performance of the rule-based strategy and the regular and robust dispatch optimization strategy. Figure 6 shows that the state-of-charge for the rule-based strategy and robust dispatch optimization strategy are higher than that of the dispatch optimization strategy using a real or perfect information forecast, showing a more conservative or risk-averse behaviour. When the pessimism level of the robust approach, represented by α, increases, the operation obtained with the dispatch optimization tends towards that of the rule-based strategy. Notably, results show that during day 144 the baseload power production is satisfied only when using the rule-based strategy and the robust dispatch optimization strategy with $\alpha = 2$. This results confirms that the use of a pessimistic forecast encourages a conservative storage operation.

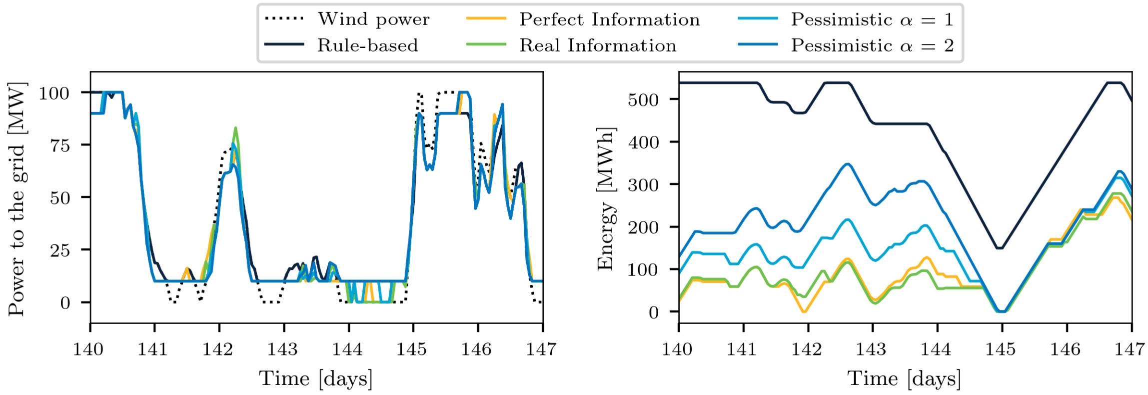

Figure 6: Power sent to the grid and energy level of the storage system for the rule-based strategy and dispatch optimization strategy using different forecast signals for the reference site.

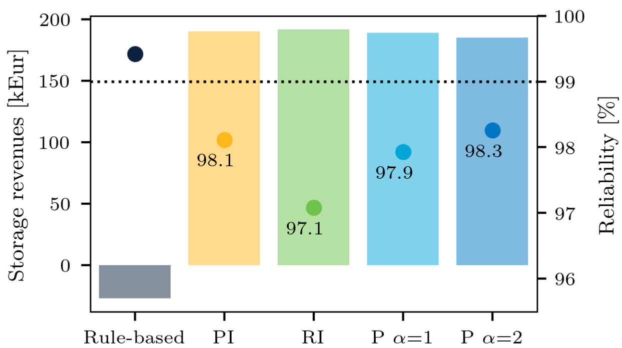

Figure 7: Reliability (dots) and storage revenues (bars) over one year for the reference site for the rule-based and optimization strategies using perfect (PI), real information (RI), and pessimistic (P) forecasts.

The storage revenues and reliability of the baseload power production calculated over the year are shown in Figure 7. The rule-based strategy shows the lowest revenues, due to its tendency to keep the storage full without taking advantage of the forecast information. Instead, the optimization-based strategies all present positive revenues. Interestingly, the storage revenues are not impacted significantly by the type of forecast. This suggest that the baseload constraint is driving the optimal operation of the storage.

In addition, the reliability decrease between the perfect and real information cases due to the impact of errors in the forecast. However, the use of a robust approach with a pessimistic forecast results in an increase in reliability, with a slight change in revenues, showing the effectiveness of the proposed method. We note that the reliability is lower than the target for the cases based on dispatch optimization. This is because the reliability constraint is enforced on a limited time window, and not on the entire year. Furthermore, the reliability is below target even for the perfect information case, showing the negative impact of a limited forecast window.

4.2 All sites

Figure 8 generalizes these results for 18 offshore sites in Europe. For each site, the relative difference in storage revenues and difference in reliability compared to the perfect information case are plotted. Results show that the forecast uncertainties associated with the real information forecast lower the reliability for all sites, between -0.4 and -1.5 points. Similarly to Figure 7, we see an increase in reliability when using a pessimistic version of the forecast. In the more conservative case ($\alpha = 2$) the reliability is higher than for the perfect information forecast for half of the sites. On average, the reliability is increased by 0.7 points for $\alpha = 1$ and by 0.9 points for $\alpha = 2$ compared to the real information case. Instead, the

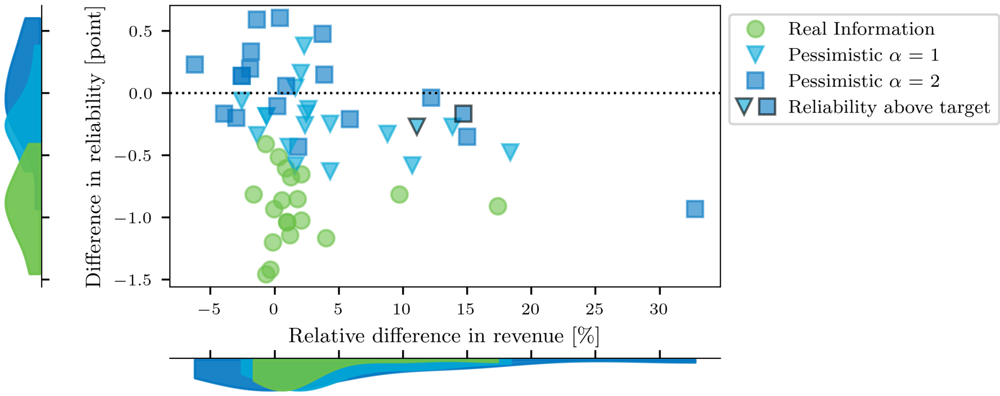

Figure 8: Reliability and revenues of the dispatch optimization based on real information and pessimistic forecasts for 18 offshore sites in Europe, relative to the dispatch optimization using perfect information forecast

impact on revenues does not show a specific trend. On average, the revenues increase by around 2% for the pessimistic cases, but with a large spread in the data. Notably, there is an outlier where the storage revenues with the pessimistic forecast for $\alpha = 2$ are 33% higher than with the perfect information forecast. Overall, these results show that a robust dispatch strategy using a pessimistic forecast can effectively mitigate the impact of forecast error on the reliability of the baseload power production.

The results for the rule-based strategy are not reported in the figure: it is the worst approach for all sites, with a decrease in revenues between -100% and -250% compared to the perfect information case. However, this strategy achieves the target reliability for all sites.

As can be seen on Figure 8, the target reliability of 99% is reached for only one site using the pessimistic forecasts. These results suggest that the storage system is not able to both deliver baseload power with a given reliability and generate positive revenues. In the dispatch optimization problem, the balance between reliability and revenues can be calibrated with the parameter μ. For the results presented here, $\mu = (n+m)P_{\mathrm{BL}}\max_i(\lambda_{j+i})$. This value means that if the reliability is below target, this penalty leads to an apparent loss of revenue equal to selling power to the highest price in the period. As such, our results suggest that satisfying the reliability target would lead to a much larger revenue loss and possibly negative revenues as with the rule-based strategy.

5 Discussion

Future work is needed to understand why the revenues increase for some sites and decrease for others. Furthermore, further development on the formulation of a reliability constraint for dispatch optimization would be beneficial to ensure that the target reliability is reached. Finally, this work uses a simple model for wind farm power production. Using a higher-fidelity model would make our analysis more precise and realistic.

6 Conclusion

This study demonstrates the feasibility of providing a reliable baseload power from wind energy when information about future wind power is limited in time and uncertain. Our results show that the reliability corresponding to a baseload production can be increased when using a dispatch optimization method using a pessimistic version of the power forecast, following a robust formulation of the optimization problem. In particular, the impact of forecast uncertainties can be efficiently mitigated by the proposed method. We further show that the impact on revenues is limited on average.

Finally, our results demonstrates that the proposed robust dispatch method allows the storage dispatch to shift its priority from satisfaction of baseload power in time of need and revenue maximization through arbitrage any other time. This ability to automatically adapt the goal during operation is a clear strength of dispatch optimization strategies over rule-based strategies.

Code and data availability

The wind speed and wind direction forecast data used to generate the results presented in this work are available open-source in the data repository associated with [17]. The research results can be reproduced with the open-source code SHIPP available at https://github.com/jennaiori/shipp [18].

Acknowledgements

The results presented in this work are based on data from the European Centre for Medium-Range Weather Forecasts (ECMWF). This work is part of the Hollandse Kust Noord wind farm innovation program. Funding was provided by CrossWind C.V., and content support was provided by Shell.

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