Key Performance Indicators of Wind Farm: Implications for Energy Storage Sizing

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Abstract. The increasing penetration of wind energy requires robust indicators to characterize variability and to guide the integration of storage technologies. This study presents a KPI-based comparative framework applied to measured hourly data from a 140 MW wind farm in Morocco over one full year. The framework quantifies energy yield, variability, and operational performance, linking these empirical indicators to optimal storage sizing. Results show an annual generation of 458 GWh, corresponding to an average output of 52.3 MW and a capacity factor of 37.4%. Availability reached 87.6%, excluding grid curtailments, and operation near nominal power occurred in less than 0.2% of the year. Monthly capacity factors varied between 24.5% and 49.7%, revealing strong seasonal fluctuations. Ramp analysis indicates that 95% of hourly ramps remain below ±21 MW/h, while extreme events reached ±139 MW/h. These dynamics were translated into storage requirements, showing that a battery of approximately 40 MW / 160 MWh can handle short-term and diurnal variability, whereas hydrogen storage with ≈120 MW electrolyzers and multi-day capacity is required for seasonal balancing. The hybrid configuration demonstrates superior performance, achieving renewable utilization above 95% and curtailment below 2%. This work introduces a novel, KPI-driven, data-validated methodology that links operational metrics with techno-economic design, offering a practical tool to optimize hybrid storage strategies and accelerate large-scale renewable integration in Morocco and comparable power systems.

Keywords: *Wind energy integration; Key performance indicators (KPIs); Energy storage dimensioning; Lithium-ion batteries; Green hydrogen; Hybrid storage systems.*

1. Introduction

Wind energy is becoming a cornerstone of decarbonization strategies worldwide due to falling costs and large resource potential. However, unlike dispatchable generation, wind output fluctuates continuously with meteorological conditions. This variability creates a mismatch between generation and demand, posing operational and planning challenges for power systems [1].

To address these challenges, researchers and practitioners have increasingly relied on Key Performance Indicators (KPIs) to characterize wind resource quality, operational performance, and integration potential [2]. Indicators such as the capacity factor (CF) assess energy yield and economic viability, while power duration curves (PDCs) highlight guaranteed output levels at different quantiles [3]. Beyond energy-based metrics, diurnal profiles reveal systematic daily fluctuations relevant for scheduling storage or flexible loads [4]. Likewise, ramp rate distributions quantify short-term variability and the resulting requirements for reserves or fast-response storage [5]. Collectively, these KPIs provide a structured framework for linking real-world wind data to system-level design and operation [6] [7].

Recent studies have shown that the integration of wind energy with storage technologies significantly enhances the value of these KPIs [8] [9][10]. However, most of these KPI frameworks are developed using simulated or modeled data, which often fail to capture curtailments, extreme ramps, and real operational dynamics [11]. For example, capacity factor and ramp metrics have been directly applied to determine the sizing of batteries for short-duration balancing and to define electrolyzer operating ranges for hydrogen production [12]. Power duration curves have been used to estimate the minimal storage capacity required to cover periods of low wind generation,

while availability metrics provide insight into curtailment risk and infrastructure utilization [13]. Such KPI-driven approaches are increasingly recognized as essential tools not only for academic assessment but also for guiding investment and policy decisions in renewable-dominated systems [14] [15]. This creates a need to test KPI methodologies on real operational datasets to ensure their accuracy and practical applicability [12] [16].

This study addresses this gap by applying a KPI-based framework to real hourly production data from a 140 MW wind farm in Morocco. Unlike previous work relying on simulated profiles, this analysis directly links operational indicators to storage dimensioning for both battery and hydrogen systems. This empirical approach improves the realism of storage sizing and supports more informed investment and policy decisions.

Morocco provides a relevant case study, as it combines strong wind resources with ambitious green hydrogen strategies. The methodology developed here quantifies variability, translates it into storage requirements, and proposes a hybrid battery–hydrogen strategy. The remainder of this paper is structured as follows: Section 2 presents the methodology and KPI framework, Section 3 reports the main results, Section 4 discusses storage and policy implications, and Section 5 concludes with perspectives for future work.

This study develops a KPI framework that integrates global and monthly capacity factors, power duration curves, diurnal variability, ramping behaviour, and availability metrics. These indicators are directly translated into storage requirements, with lithium-ion batteries addressing short-term balancing and hydrogen storage covering long-duration needs. The key contribution of this work is to bridge KPI analysis with practical storage dimensioning through a fully empirical approach based on real wind farm data. This methodology provides a reproducible and validated tool for aligning operational performance metrics with techno-economic storage design, supporting both system planning and policy strategies for large-scale renewable integration.

2. Methodology

This section describes the dataset, preprocessing steps, and the Key Performance Indicators (KPIs) framework applied to the 140 MW wind farm data. It also explains how these KPIs are used to derive storage dimensioning requirements for batteries, hydrogen systems, and hybrid configurations. This integrated approach provides a data-driven foundation for linking real operational behavior with energy storage sizing, ensuring that the analysis reflects realistic grid conditions rather than simulated assumptions.

2.1 Wind Farm Dataset

The analysis is based on measured hourly production data from a 140 MW wind farm in Morocco, covering an entire year. The dataset represents the net active power delivered to the grid, expressed in megawatts (MW) [17]. It has a temporal resolution of one hour, resulting in a full-year dataset of 8760 records. The raw measurements contain missing entries, occasional negative values due to sensor errors, and periods of curtailment. The choice of a real operational dataset ensures that the derived KPIs reflect the true variability and availability of the wind resource under actual grid conditions. A representative two-week excerpt of the time series is shown in Figure 1, which illustrates the intermittent nature of wind generation and its short-term fluctuations. The use of empirical data strengthens the reliability of the subsequent KPI analysis and allows the results to be directly validated against real operational performance rather than modelled approximations.

The dataset covers a full annual cycle, capturing both diurnal and seasonal variability that are critical for evaluating storage performance and long-term balancing needs.

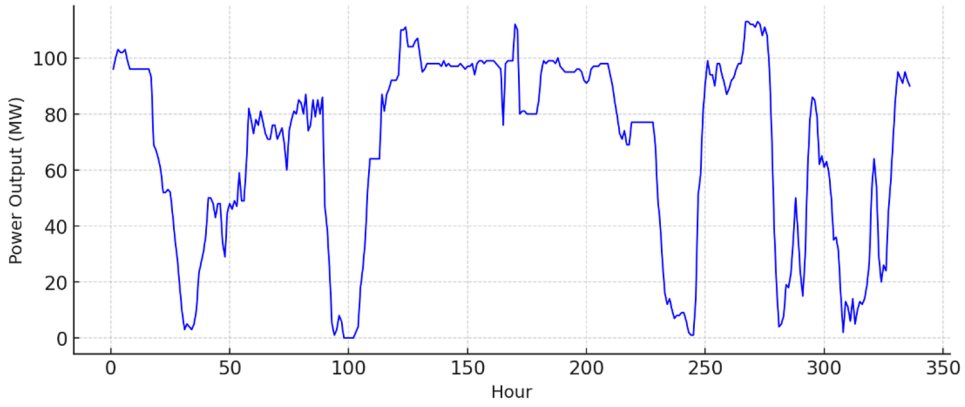

Fig.1. Hourly power output over two weeks, showing strong intraday fluctuations and ramps that highlight the need for short-term storage.

Figure 1 illustrates the hourly wind power output of the 140 MW wind farm over a representative two-week period. The profile shows strong intraday variability and several ramping events exceeding 40 MW. This variability highlights the need for short-term flexibility mechanisms such as battery storage and provides the basis for the KPI and sizing analyses presented in the following sections.

2.2 Data Preprocessing

The dataset was standardized to Coordinated Universal Time (UTC) at hourly resolution, cleaned of negative values and spurious spikes, and linearly interpolated for short gaps. Power outputs were normalized to the rated capacity of 140 MW, and the series was resampled to obtain exactly 8760 hourly records. These steps ensured a consistent and reliable dataset, suitable for KPI calculations and reproducible across other wind farms.

The adopted cleaning and normalization process preserves the statistical structure of wind fluctuations, ensuring that ramp events, curtailment periods, and downtime are realistically represented.
The reported availability (87.6%) excludes grid-related curtailment, so the KPIs represent intrinsic turbine performance. Including curtailment would slightly reduce the capacity factor (by approximately 1–2%) but does not alter the overall conclusions.

2.3 KPI Framework

The KPIs selected for this study are designed to capture energy yield, variability, and operational constraints. They provide a standardized and comparable framework for assessing wind farm behavior under real operating conditions, forming the basis for translating variability into storage design parameters.

2.3.1 Total Energy and Capacity Factor

The total energy produced is computed as:

$$Etot = \sum_{t=1}^{T} P(t) \cdot \Delta t \qquad (1)$$

Where:

- E is the total energy (MWh),
- P_t is the power output at hour t (MW),
- Δt is the time step (h).

The capacity factor (CF) is defined [18] as:

$$CF = \frac{\bar{P}}{P_{rated}} = \frac{E_{tot}}{P_{rated} \cdot T} \quad (2)$$

with $P_{rated} = 140$ MW and T the total observation period. Both global CF and monthly CF are reported.

Monthly CF values are used to assess seasonal variability, which provides essential information for estimating long-term hydrogen storage requirements.

2.3.2 Power Duration Curve (PDC)

The PDC is obtained by sorting all hourly outputs in descending order. For each quantile q, the exceedance probability P_q is calculated [19]. Key values such as P50 (median output) and P90 (output exceeded 90% of the time) are derived:

$$P_q = \text{Quantile}(P(t), q) \quad (3)$$

Where:

P_q is the power at quantile q (MW),

These indicators provide probabilistic guarantees of generation and guide the minimum sizing of electrolyzers and storage systems.

2.3.3 Diurnal Profiles

The diurnal profile is derived by averaging hourly values across all days:

$$P_{diurnal}(h) = \frac{1}{N_d} \sum_{d=1}^{N_d} P(d, h) \quad (4)$$

Where:

P_h is the average power at hour h (MW),

h is the hour of day (0–23), and N_d is the number of days [20].

This indicator highlights systematic intra-day patterns relevant for scheduling electrolyzer operation and battery charging.

2.3.4 Ramp Rate Distribution

Hourly ramp rates are calculated as:

$$\Delta P(t) = P(t) - P(t-1) \quad (5)$$

Where:

ΔP_t is the ramp between hour t and $t-1$ (MW/h).

A histogram of ΔP provides the distribution of short-term variations. Statistical measures such as mean, standard deviation, 95th and 99th percentiles are reported. These values quantify the flexibility requirements for batteries or fast-response hydrogen systems.

2.3.5 Availability and Nominal Proximity

Availability is defined as the proportion of hours where generation is above 1% of rated power:

$$Avail = \frac{\sum_t 1[P(t)>0.01\cdot P_{rated}]}{T} \quad (6)$$

Nominal proximity is defined as the shar of hours where generation exceeds 95% of rated capacity:

$$Nominal = \frac{\sum_t 1[P(t)\geq 0.95\cdot P_{rated}]}{T} \quad (7)$$

Where:

A is availability (%),
N is nominal proximity (%),

These metrics provide a comprehensive basis for assessing wind farm performance and for linking operational variability to storage requirements. The global results derived from the 140 MW wind farm dataset are summarized in Table 1, which reports the total annual energy, mean power, capacity factor, availability, nominal proximity, and valid observation hours.

Table 1. Global Key Performance Indicators

Indicator	Value	Unit
Total Energy E_{tot}	458 426.00	MWh
Mean Power $\bar{P}$	52.33	MW
Capacity Factor (CF)	37.38	%
Availability	87.64	%
Nominal Proximity	0.18	%
Valid Hours	8 760	h

2.4 Storage Dimensioning Approach

The extracted KPIs are directly linked to storage requirements:

- Batteries:
  - Ramp rates determine the power rating (MW).
  - Diurnal variability determines energy duration (2–4 h typical).
- Hydrogen systems:
  - PDC quantiles (P90, P95) guide electrolyzer sizing.
  - Monthly CF variation informs storage volume requirements (6–168 h equivalent).
- Hybrid systems:
  - Batteries smooth short-term fluctuations.
  - Hydrogen covers extended deficits.

This methodology ensures that real-world wind KPIs are translated into actionable storage design parameters.

3. Results

The analysis of the 140 MW wind farm production data provides a set of key performance indicators (KPIs) that characterize its energy yield, variability, and operational constraints. These results are presented below, with emphasis on the indicators most relevant for subsequent storage dimensioning.

3.1 Seasonal and Monthly Performance

Monthly capacity factors show a wide variability, ranging from 24.5% in December to 49.7% in June. This highlights the strong seasonal dependence of wind resource availability and underlines the need for long-duration storage solutions to compensate for deficits in low-wind periods. The annual variation is depicted in Figure 2.

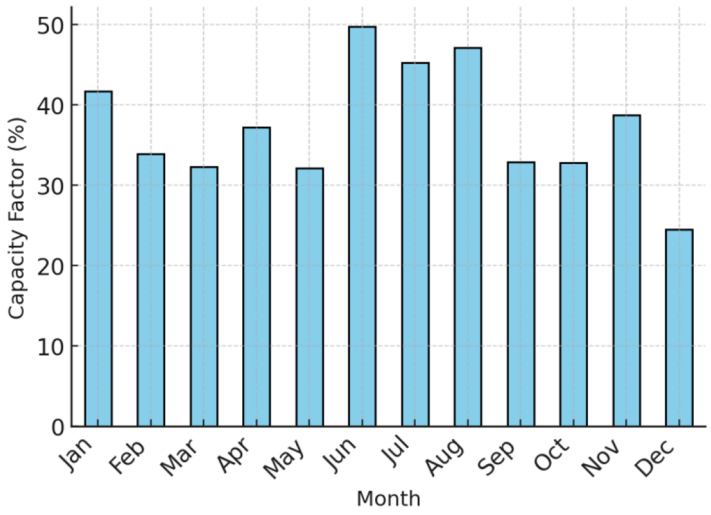

Fig. 2. Monthly capacity factors, revealing clear seasonal variability with a summer peak and winter deficit, relevant for long-duration storage sizing.

The monthly capacity factor profile reveals a clear seasonal pattern, peaking in summer and decreasing in winter. This seasonal gap implies that short-duration storage alone is insufficient to ensure continuity of supply, underscoring the role of long-duration solutions like hydrogen.

3.2 Power Duration Characteristics

The Power Duration Curve (PDC) provides information on guaranteed output levels. Results show that the wind farm delivers more than 42 MW (30% of rated power) in 50% of the hours (P50), and above 120 MW (86% of rated power) in 10% of the hours (P90). These findings are illustrated in Figure 3, confirming that while wind output is intermittent, it ensures significant contributions to the grid for a large portion of the year.

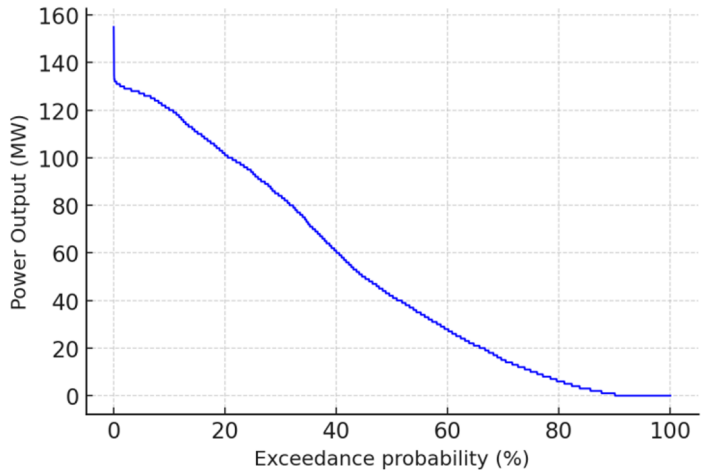

Fig. 3. Power duration curve showing P50 at 42 MW and P90 at 120 MW, providing thresholds for electrolyzer and storage sizing.

The power duration curve shows a P50 of 42 MW and a P90 of 120 MW. These threshold values can guide the sizing of electrolyzers and other downstream conversion assets to match the most frequent production ranges, improving asset utilization.

3.3 Ramp Rate Analysis

Short-term variability was assessed through the distribution of hourly ramps. Most changes remain moderate, with an average close to zero, but extreme events reached +106 MW/h and –139 MW/h**.** Percentile analysis indicates that 95% of absolute ramps are below 21 MW/h**,** and 99% below 38 MW/h. The overall distribution is illustrated in Figure 4, highlighting both the predominance of moderate variations and the presence of occasional extreme events. These results are directly relevant for sizing the power rating of batteries and for defining the ramping flexibility requirements of electrolyzers.

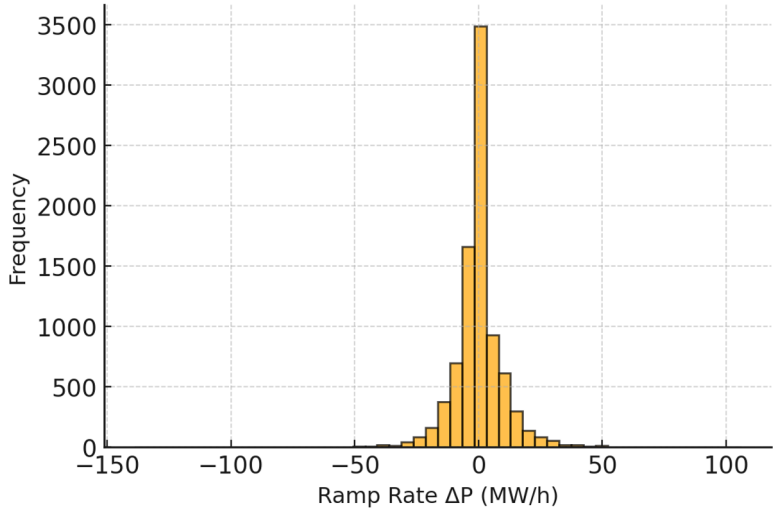

Fig.4. Hourly ramp distribution showing most events below ±21 MW and extremes up to ±139 MW, defining BESS power rating needs.

The ramp distribution indicates that most hourly ramps remain below ±21 MW, but extreme events can reach up to ±139 MW. This defines the required power rating for short-term storage to ensure stable grid injection.

3.4 Synthesis of Indicators

Overall, the KPI analysis demonstrates that the wind farm combines a solid annual capacity factor with significant seasonal fluctuations and occasional extreme ramps. These findings emphasize the importance of hybrid storage approaches, where batteries manage short-term variability and hydrogen systems ensure seasonal balancing.

4. Discussion

The results presented above demonstrate the operational characteristics of the 140 MW wind farm and provide quantitative insights for the integration of storage technologies. This section discusses the implications of the KPIs in terms of storage sizing, system design, and broader integration strategies.

The reported availability of 87.6 % excludes periods of grid curtailment. Including these events would slightly reduce the annual capacity factor (≈ 1–2 %) but would not materially affect the variability metrics or the resulting storage sizing.

The ramp rate analysis (Figure 4) shows that while most hourly changes remain moderate, extreme variations can reach ±100 MW. Such ramps define the minimum power rating that a battery energy storage system (BESS) must accommodate in order to smooth short-term fluctuations. Considering the 99th percentile of absolute ramps (≈ 38 MW/h), a battery with a power rating of about 40 MW would be adequate for covering the majority of events.

The present analysis is based on hourly resolution; sub-hourly fluctuations, while not captured here, are expected to add marginal short-term variability without significantly altering the sizing at system level. Future work will include finer temporal resolutions to assess these dynamics more precisely.

In addition, diurnal variability, with an average amplitude of ≈ 10 MW, indicates that batteries with 2–4 hours of storage duration (≈ 80–160 MWh) would provide sufficient capacity. This configuration ensures effective mitigation of intraday fluctuations, reduces ramping stress on the grid, and enhances the participation of wind power in balancing markets.

Seasonal variability is highlighted by the monthly capacity factor results (Figure 2), which range between 25 % and 50 %. Such variability cannot be fully addressed by batteries, as it requires long-duration coverage. In this context, hydrogen systems become essential.

The power duration curve (Figure 3) shows that in 10 % of the hours, the farm produces more than 120 MW, which suggests that electrolyzers sized around 120 MW could absorb high-output events without curtailment. Hydrogen storage must also be dimensioned to cover seasonal deficits, requiring capacities equivalent to several days or weeks of average production. Although less efficient than batteries (round-trip efficiency ~35–45 %), hydrogen provides the depth of storage necessary to ensure long-term system reliability.

The combination of batteries and hydrogen leverages their complementary strengths. Batteries offer fast-response, high-efficiency coverage of short-term ramps, while hydrogen provides seasonal balancing and long-duration security of supply. The hybrid approach also mitigates curtailment risk by allocating intraday variability to batteries and sustained excess generation to hydrogen.

This hybrid sizing strategy aligns with benchmark studies [5] [12], which show similar electrolyzer and BESS sizing ratios for wind farms of comparable capacity, reinforcing the technical robustness of the proposed configuration.

This dual strategy aligns with Morocco's ambitions for large-scale deployment of green hydrogen while simultaneously supporting grid flexibility. By sizing the hybrid storage according to KPI-derived thresholds (≈ 40 MW / 160 MWh for batteries, ≈ 120 MW electrolyzer for hydrogen), a balanced solution is achieved that addresses both immediate operational challenges and long-term integration needs.

Beyond technical sizing, KPI-based analysis also informs investment and policy decisions. The relatively high annual capacity factor (≈ 37 %) confirms the strong wind resource, while the presence of extreme ramps underscores the need for ancillary services and flexible grid infrastructure. Storage solutions guided by KPIs can reduce overall system costs by avoiding over-dimensioning and ensuring that investments are aligned with actual operational requirements.

Future work will include multi-year datasets and sensitivity analyses to evaluate the robustness of these results under different demand profiles, market conditions, and grid constraints.

5. Conclusion

This study demonstrated how a KPI-based analysis of real operational wind farm data can be directly translated into indicative storage sizing requirements. Unlike many previous works relying on simulated profiles, this approach uses measured hourly production from a 140 MW wind farm, providing realistic insights into variability, ramping behaviour, and seasonal fluctuations.

The results highlight the complementarity between short-term battery storage and long-duration hydrogen systems. Batteries are well suited to manage fast fluctuations and ramp events, while hydrogen provides seasonal balancing and enhances long-term security of supply.

This work develops an empirical KPI-based framework that links wind performance indicators to indicative storage dimensioning, providing a practical and transparent approach that can be adapted to other sites and support preliminary planning and integration strategies in renewable-dominated grids.

Future work will extend the framework by integrating demand profiles, market signals, and grid stability constraints to evaluate the operational and economic impacts of different hybrid storage pathways. Such developments will further strengthen the role of KPI-based approaches as decision-support tools for large-scale renewable integration.

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