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Adapting Overall Equipment Effectiveness to the Wind Energy Sector: The OEE_{RE} Approach

Oscar Muñoz [1,*], Diego Antolín-Cañada [2], María Pilar Lambán [3] and Juan Carlos Sanchez [1]

[1] TECNALIA, Basque Research Technology Alliance (BRTA), 50018 Zaragoza, Spain; jcarlos.sanchez@tecnalia.com
[2] Grupo de Electrónica de Potencia y Microelectrónica (GEPM), Escuela Universitaria Politécnica de la Almunia (EUPLA), Universidad de Zaragoza, 50009 Zaragoza, Spain; dantolin@unizar.es
[3] Department of Design and Manufacturing Engineering, University of Zaragoza, 50009 Zaragoza, Spain; plamban@unizar.es
* Correspondence: oscar.munoz@tecnalia.com

Abstract

The Overall Equipment Effectiveness (OEE) indicator is a widely used key performance indicator (KPI) in industrial environments to assess equipment efficiency through the combination of availability, performance, and quality metrics. However, its direct application to renewable energy systems presents significant limitations due to the stochastic nature of the energy resource and the operating characteristics of wind turbines. This paper proposes an adaptation of Overall Equipment Effectiveness (OEE) for the wind energy sector, referred to as Overall Equipment Effectiveness for Renewable Energy (OEE_{RE}), in which the traditional availability, performance, and quality factors are reformulated to reflect the operational reality of utility-scale wind turbines. The proposed methodology defines the OEE_{RE} indicators using variables directly available from standard wind farm Supervisory Control and Data Acquisition systems (SCADA), enabling practical implementation without additional instrumentation. Special attention is devoted to the calculation of the performance indicator, which incorporates manufacturer power curve normalization according to IEC 61400-12 recommendations, including air density correction and turbulence intensity compensation. The quality indicator is derived from turbine-level electrical parameters associated with power generation performance. The methodology is validated using operational measurements collected from seven wind turbines within a commercial wind farm. The results demonstrate the feasibility of the proposed approach and show that performance and quality are the dominant contributors to OEE_{RE} variability, while availability remains close to unity under normal operating conditions. The proposed framework provides a practical and interpretable KPI for monitoring wind turbine efficiency, identifying operational deviations, and supporting performance optimization in renewable energy assets.

Keywords: Overall Equipment Effectiveness; OEE_{RE}; key performance indicators (KPIs); metric adaptation; renewable energy systems; wind turbines; air density correction; power curve normalization; SCADA

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1. Introduction

The increase in wind power generation in recent decades makes the industrial development of this technology particularly interesting. Figure 1 shows the increase in wind power generation worldwide, in Europe and in the United States [1]. This information, taken from Our World in Data, whose database can be found at [2], shows the current

production trend for this type of energy. Furthermore, WindEurope [3] estimates that by 2024, 20% of the electricity generated in Europe will come from wind energy.

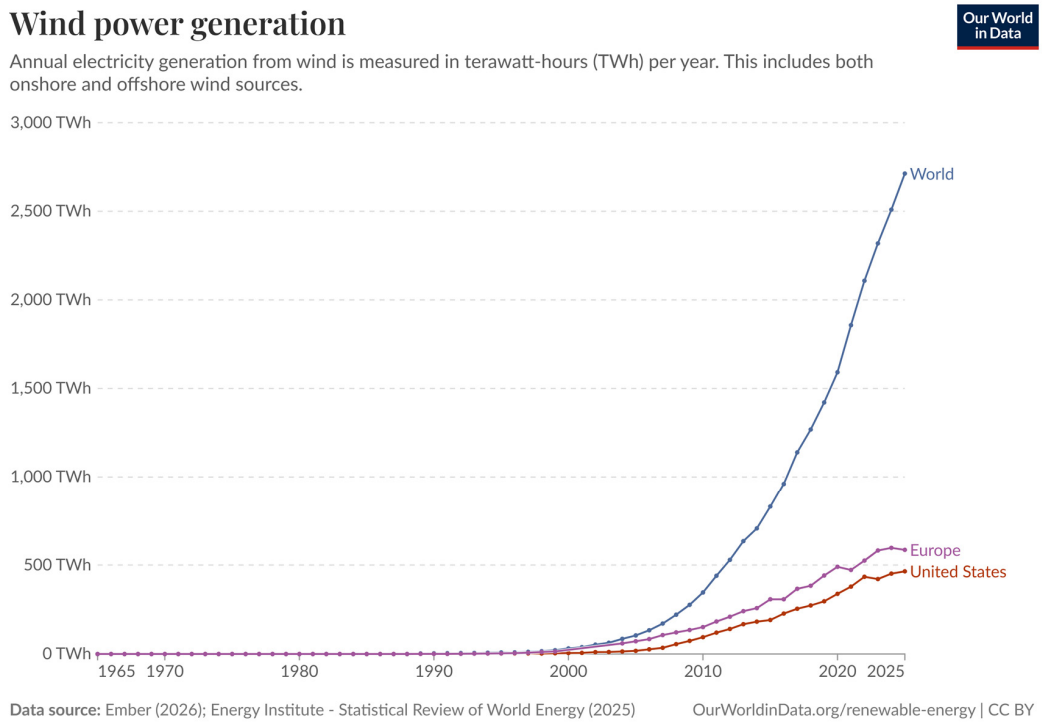


Figure 1. This image represents the growth of wind power generation worldwide. Image taken from OurWorldInData [1,2].

Given the growing development of this industry, it is necessary to develop tools that focus on improving equipment productivity, reducing losses and, ultimately, optimizing wind power generation systems.

A widely used tool in the industry that allows the actual efficiency of production equipment to be quantified in a standardized way against its theoretical capacity, enabling the industrial sector to measure the productivity and efficiency of equipment [4], is Overall Equipment Effectiveness (OEE), proposed by Nakajima in 1988 [5]. This tool is essential for manufacturing companies to have indicators that allow them to detect possible areas for optimization and improvement.

Throughout the last ten years, the scope of this indicator has broadened well beyond the manufacturing context in which it originated, as the body of literature compiled in [6] makes evident. Drawing on that review, the same authors argue that the indicator can legitimately inform strategic decisions at the corporate level, since a properly contextualized formulation enables the joint assessment of how efficiently material, financial and human resources are being deployed. Wind power generation is among the sectors in which this possibility has begun to attract attention. Nevertheless, transposing the indicator to such an environment is far from straightforward: it presupposes a detailed examination of the underlying process—in this instance, the conversion of wind energy into electricity—so as to identify which losses, operating variables and influencing factors must be incorporated, always within the limits imposed by the parameters that can actually be measured or derived. The resulting framework could even be extended to encompass environmental descriptors such as the carbon footprint. Considered as a whole, these metrics yield an integrated picture of operational performance and ultimately serve the two fundamental aims of any productive activity: to raise productivity and to curtail waste.

As early as 2003, in [7], the use of OEE in offshore wind farms was proposed. In this paper, OEE is adapted from the traditional industrial perspective to an offshore wind farm to quantify the effectiveness of the operation and maintenance process, measuring how much available energy actually ends up becoming valuable energy, that is, energy delivered and sold to the grid. In the wind power context, it is not interpreted as the conventional manufacturing metric, but rather as an indicator of operational effectiveness that quantifies the impact of planned outages, unplanned failures, technical efficiency losses and potential reductions due to power quality on the valuable electrical energy ultimately delivered to the grid. To this end, it measures and quantifies the electrical energy delivered/sold at the grid connection point, that is, the energy actually fed into the grid and billable.

The use of OEE in the renewable energy sector is not limited to wind farms; its application has also been proposed for photovoltaic panels [8]. In this 2021 publication, the authors propose using OEE to analyze the operational performance of each panel module under real production conditions, as manufacturers typically provide data under standard conditions—which sometimes bear little resemblance to real-world conditions—in order to estimate performance losses in photovoltaic panels operating outside standard conditions. This transforms OEE into an energy diagnostics tool. As this study concludes, this research was conducted to evaluate the performance indices of a specified panel type.

Returning to the application of OEE in renewable energy generation through wind power and offshore wind farms, in 2023, the authors of [9] conducted a review of the use of OEE as a metric for assessing operational losses in wind farms from an economic perspective. To this end, they classified and organized the operational losses described in the literature within the classical definition of OEE.

As discussed in the cited article, OEE provides a versatile framework for technology optimization by relating equipment productivity to the identification of and reduction in operational losses. Its simplicity and adaptability support its transfer to different application domains, including energy systems, where it can assist in decision-making and continuous improvement processes.

This article proposes adapting the classic OEE mathematical model proposed by Nakajima to the specific requirements of renewable energy, which we will refer to as Overall Equipment Effectiveness for Renewable Energy (OEE_{RE}), with a focus on its application to an onshore wind farm.

The main objective of this work is to identify the key performance indicators (KPIs) required to calculate the three parameters required for the OEE calculation: availability (A), performance (P) and quality (Q).

Unlike the study presented in [9], which analyzes performance indicators at the wind farm level in offshore wind farms from the perspective of the causes leading to a shortfall in generation—a summary of which is shown in Figure 2—this article aims to provide a classification of key performance indicators (KPIs) and their effect on the parameters used to calculate OEE based on measurements of electrical parameters in the turbines, focusing on the measurement of the electrical parameters that reflect these indicators. To this end, an alternative classification will be proposed, and calculations of availability, performance and quality will be presented. The proposed methodology is applied and validated using data from a real onshore farm.

It is important to note that when selecting KPIs, these must be parameters that can be measured using the wind farm's control systems; in other words, they must be available in the data collected by the farm's monitoring systems. This is normally done via Supervisory Control and Data Acquisition (SCADA). Whilst, at first glance, it may seem worthwhile to add more sensors and monitoring systems to control and measure additional parameters that contribute to better data on the wind turbine's performance, this is not practical due

to the volume of data and the increased costs of the control system. This situation is well known to the team behind this work, which contributed to the development of a wind-turbine-monitoring system for research [10]. The key point is that the data must be available within the industrialized monitoring system so that the proposed formulation is compatible with wind farms currently in operation.

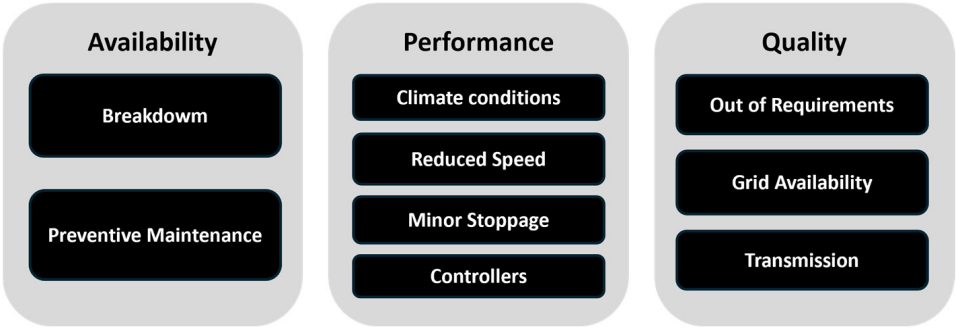


Figure 2. Classification of the main operational losses affecting OEE in wind farms, based on [9].

This article is organized as follows: Section 2, in the first subsection, sets out the proposed key performance indicators (KPIs) used to determine the different OEE parameters. The second subsection describes the wind-turbine-monitoring system, the parameters measured, the distribution of wind turbines in the case study wind farm and its wind rose. Section 3 presents the OEE results after analyzing the data collected for each parameter. Finally, Section 4 discusses the results and conclusions of this study.

2. Materials and Methods

To establish the KPIs that affect each of the OEE calculation parameters, the losses occurring in the wind turbine that can be measured by the SCADA system are examined, and examples of these losses are provided. This preliminary analysis is set out in Table 1.

Summarizing the main losses graphically, in a similar manner to that shown in Figure 2, Figure 3 was obtained. This allows for a comparison of the contributions of the proposed system. With regard to availability, wind curtailment is taken into account. In terms of performance, environmental factors, wear and tear, sensor failures and control failures are observed as deviations from the machine's nominal performance curve under operating conditions. Finally, with regard to quality, parameters that directly affect it but differ from the connection to the electricity grid are taken into account.

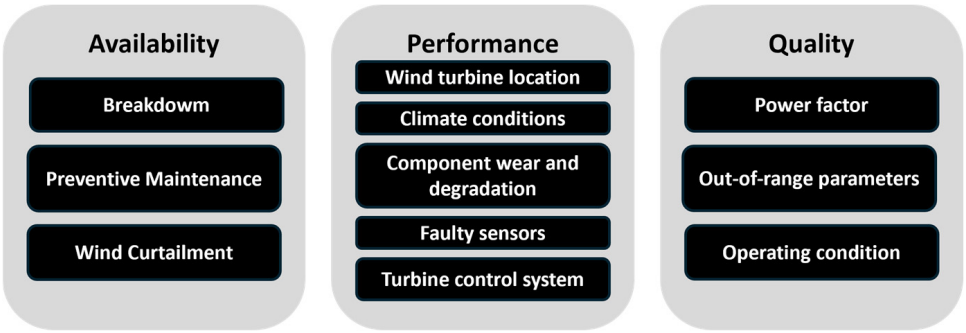


Figure 3. Block diagram summarizing the losses that affect proposed OEE_{RE}.

The following subsections explain how the adaptation of the OEE_{RE} was implemented and carried out.

Table 1. This table shows the preliminary analysis of KPIs for the transition from OEE to OEE_{RE}.

	Losses	**Examples**
Availability	Breakdown	Machine failures Corrective maintenance
	Preventive maintenance	Preventive maintenance actions on the turbine Maintenance operations of the wind farm
	Wind curtailment	Curtailment due to limited grid capacity
Performance	Wind turbine location	Landscape characteristics Wake effects
	Climate conditions	Changes in air density Wind direction variability Wind turbulence Wind shear Wind gusts Extreme temperatures Blade icing Seasonal conditions
	Component wear and degradation	Blade damage Hydraulic system degradation Gearbox lubrication deficiency Gearbox mechanical degradation Mechanical and electrical generator faults Transformer thermal degradation
	Faulty sensors	Anemometer (wind speed and direction) Rotor speed sensor
	Turbine control system	Inappropriate control parameters Software updates
Quality	Power factor	Power factor performance
	Out-of-range parameters	Overvoltage and undervoltage in the generator Grid frequency deviations
	Operating condition	Generator operating quadrant

2.1. Fundamentals of OEE for Renewable Energies: Wind Energy

The application of the classic OEE postulated by Seiichi Nakajima to determine the current efficiency of production equipment needs to be adapted for use in the renewable energy sector, focusing on wind power generation. To this end, a new OEE is defined, called OEE_{RE}. In the following subsections, the definitions and equations of OEE for the adapted terms of availability, performance and quality are justified.

2.1.1. Availability of Renewable Energy (A_{RE})

Nakajima posits availability (A) as the operating time of a production line, allowing deviations in the planned working time, the expected operating schedule, and the current working time to be detected. The actual operating time is planned time minus unexpected production stoppages (breakdowns and other unplanned stoppages), resulting in Equation (1):

$$\mathrm{A} = \frac{T_R}{T_O} = \frac{T_O - T_S}{T_O}, \tag{1}$$

where A is availability, T_R is the actual time of the production line, T_O is the planned operating time, and T_S is the unplanned downtime.

Applying this equation to wind energy requires an adjustment, as availability is subject to the availability of wind resources.

In these terms, total availability (A_{RE_T}) can be defined when there is wind or (A_{RE_WE}) when there is sufficient wind to move the wind turbine and feed energy into the grid. With this definition, Equations (2) and (3) are presented:

$$A_{RE_T} = \frac{T_R}{T_O} = \frac{T_O - T_S - T_{WE_NA}}{T_O}, \quad (2)$$

$$A_{RE_WE} = \frac{T_R}{T_O} = \frac{T_O - T_S - T_{WE_NS}}{T_O}, \quad (3)$$

where T_{WE_NA} is the time when there is no wind energy available, and T_{WE_NS} is when there is wind, but it is not sufficient to generate energy with the wind turbine.

To measure wind speed, wind turbines typically use an anemometer located in the nacelle, whose data can be accessed from the SCADA system.

As is common in industrial systems, its operation is defined in states (emergency stop, stop, start, and run), as these may depend on the control system, and, for practical purposes for the generation system, it is only relevant whether the system is in the generation phase or not; these are the states to take into account. Based on these considerations, A_{RE} can be defined as the ratio between the energy generation time and the planned operating time.

$$A_{RE} = \frac{T_G}{T_O}, \quad (4)$$

where T_G is the generation time.

2.1.2. Performance of Renewable Energy (P_{RE})

Nakajima defines performance (P) as the ratio between the ideal production time required to manufacture the produced units and the actual operating time, as shown in Equation (5):

$$P = \frac{P_M \cdot t_{ideal\ cycle}}{T_O}, \quad (5)$$

where P_M is the number of produced units, $t_{ideal\ cycle}$ is the ideal cycle time per unit and T_0 is the operating time. For energy conversion systems, performance can be expressed in terms of conversion efficiency (η), defined as the ratio between the output power (P_{OUT}) and input power (P_{IN}), as shown in Equation (6):

$$\eta = \frac{P_{OUT}}{P_{IN}}, \quad (6)$$

In wind turbines, it is more complex. Wind turbine manufacturers provide a reference power curve for each turbine model, measured in accordance with the IEC 61400-12-1 standard. The curve of the wind turbines used in this work is shown in Figure 4.

The characteristic wind power curve provided for each machine model by its manufacturer has been characterized for a specific air density. Therefore, the IEC 61400-12-2 [11] standard itself includes the method for compensating the standardized curve to the air density conditions in which the wind turbine is operating in order to calculate the machine's performance under working conditions. With this compensation, the equivalent theoretical performance is obtained (7).

$$P_{RE} = \frac{P_{Current}}{\left(P_{Theory}\right)_{EQ}}, \quad (7)$$

where $P_{Current}$ is the current power measured and provided by the machine's SCADA system, and $(P_{Theory})_{EQ}$ is the normalized equivalent power after compensating the nominal power curve for the air density of the wind turbine.

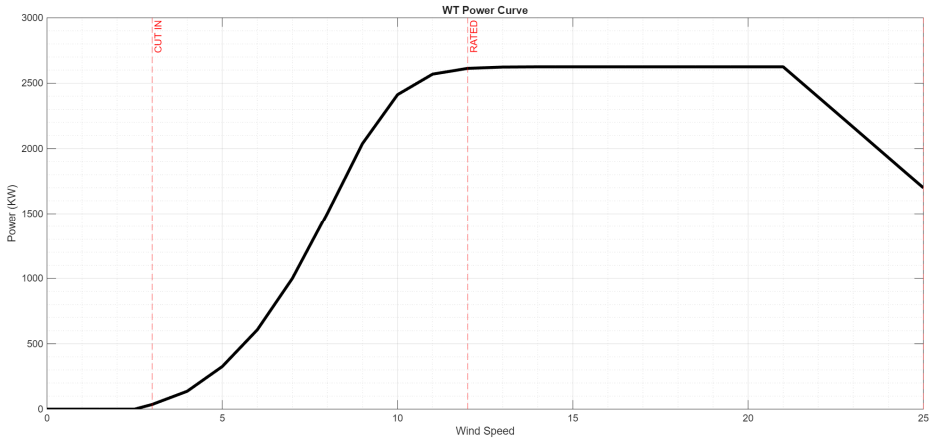


Figure 4. Example of a standard power curve for a wind turbine.

As indicated in the IEC standard for normalizing data, it is necessary to calculate air density in 10 min periods or bins. The equation for determining density is given by Equation (8) and is included in IEC standard IEC 61400-12-2 [11].

$$\rho_{10\text{min}} = \frac{1}{T_{10\text{min}}}\left(\frac{B_{10\text{min}}}{R_0}\cdot\varphi\cdot P_w\cdot\left(\frac{1}{R_0}-\frac{1}{R_w}\right)\right), \tag{8}$$

where $\rho_{10\text{min}}$ is the average air density over ten minutes, T is the average absolute air temperature over 10 min in Kelvin (K), B is the average atmospheric pressure over 10 min in Pascals (Pa), phi is the relative humidity (ranging from 0 to 1), R_0 is the constant for dry air gases (287.05 J/(kg·K)), R_w is the constant for water vapor gases (461.5 J/(kg·K)) and P_w is the vapor pressure. The vapor pressure is calculated by Expression (9):

$$P_w = 0.0000205\cdot e^{0.0631846\cdot T}, \tag{9}$$

where ρ_0 is the vapor pressure (P_w), which depends on the average air temperature T.

The standard specifies that it is not necessary to use specific relative humidity data to obtain the standardized curve, although its use is recommended. As the park under study for the validation of $\text{OEE}_{\text{RE_WE}}$ use in wind energy does not have direct data, the relative humidity of the area is obtained from open data from surrounding weather stations. Barometric pressure is also not available in the wind turbine's SCADA information, so it must be estimated. To do this, the geographical position of the tower and its height are used to obtain an approximate value for calculating air density.

As the wind turbines in the park under study have active power control, normalization must be applied to wind speed according to Equation (10).

$$V_n = V_{free}\cdot\left(\frac{\rho_{10\text{min}}}{\rho_0}\right), \tag{10}$$

where ρ_0 is the density of the reference air, which is incorporated into the manufacturer's power curve (normally 1.225 kg/m^3), V_n is the normalized wind speed, and V_{free} is the wind speed measured in the nacelle by the anemometer, whose information is collected by the SCADA.

If no information is available regarding the effect of turbulence intensity on the wind turbine, or if there is no information available to compensate for this effect, the performance is obtained from Equation (7). Here, the measured power is obtained via the SCADA system, and the equivalent normalized power is derived by normalizing the speed using Equation (10) and the power curve provided by the manufacturer.

Alternatively, if the turbulence intensity is known, the equivalent power generated can be obtained according to the normalized power curve. This correction was included in Annex M of the 2017 version of the IEC 61400-12-1 standard [12]. This compensation is relevant for obtaining more accurate values of annual energy production (AEP) and has been studied by various authors [13–15]. The method applied in this work is set out in the standard, applying Equation (11):

$$P_{Current_{EQ}} = P_{Current} + TI_K \cdot (TI_{REF} - TI_{Current}), \quad (11)$$

where $P_{CurrentEQ}$ is the equivalent power according power curve normalization, $P_{Current}$ is the average power recorded by the SCADA during the evaluation period, TI_K is the turbulent intensity compensation factor that is obtained empirically, TI_{REF} is the reference turbulence intensity (typically 0.1) and $TI_{Current}$ is the turbulence intensity measured during the target period. Finally, the equation used to determine the performance parameter for renewable energy is given in Equation (12):

$$P_{RE} = \frac{P_{Current_{EQ}}}{\left(P_{Theory}\right)_{EQ}}, \quad (12)$$

2.1.3. Quality of Renewable Energy (Q_{RE})

With the term "quality," Nakajima aims to detect defects in the production process, rework, and defective production starts. With this premise, he defines quality as the ratio of the number of correctly manufactured parts or products (P_{CM}) to the total number of parts manufactured (P_M). This relationship is shown in Equation (13):

$$Q = \frac{P_{CM}}{P_M}, \quad (13)$$

In wind energy systems, the concept of manufactured products is not directly applicable, since wind turbines continuously generate electrical energy that is delivered to the power grid rather than discrete products.

However, the parameters that define the quality of the electricity grid are often set out in specific regulations. It should be noted, however, that the approach proposed in this study for analyzing OEE_{RE} is geared towards analyzing each turbine independently; consequently, these parameters are not directly subject to grid connection regulations. Furthermore, the parameters to be taken into account must be accessible in the SCADA system; otherwise, they cannot be considered, as there is no access to current values.

The definition of the OEE_{RE} quality parameter (Q_{RE}) is established by taking into account the parameters available for each wind turbine, which are typically acquired via the SCADA system of a wind farm, resulting in Equation (14):

$$Q_{RE} = PF \cdot FVFR \cdot GR \cdot THDR, \quad (14)$$

where PF is the power factor, $FVFR$ is the frequency/voltage fault ratio, and GR is the generation ratio.

The relevance and requirement for measuring the power factor ($\cos\varphi$) is set out in standard IEC 61400-21-1 [16]; whilst its consideration is extensive, it is worth noting that at the nominal operating speed, the PF must be equal to 1.

Similarly, the EN 50549 standard [17,18] sets out the requirements for a grid-connected generation system regarding deviations in the frequency of the generated voltage from the nominal frequency. The standard stipulates that the nominal range is between 49.5 Hz and 50.5 Hz, whilst the system is permitted to operate continuously within the range of 49 Hz to

51 Hz; outside these ranges, the system must apply protection techniques, which may even lead to the system disconnecting under certain conditions and depending on the duration spent outside these ranges. The FVFR defines the ratio of the wind turbine's generation time spent within the nominal range. Under ideal conditions, this value will be 1.

The GR (generation ratio) refers to the time the wind turbine spends operating in both the inductive and capacitive generation quadrants, compared with the time it spends operating in both quadrants as a motor. The ability to operate in these two quadrants depends on both the machine and the control system implemented, but modern wind turbines, thanks to current inverters, are capable of operating in both generation quadrants. In older machines, the generation quadrant could only be the inductive one. Ideally, this parameter should be 1 or close to 1.

Finally, another important KPI for determining the quality of power generation is the Total Harmonic Distortion Index (THD_I). According to the IEEE 519 standard [19], its values should be between 3% and 8%; ideally, it should be 0%. Based on these premises, the parameter used to calculate grid quality has been termed the total harmonic distortion ratio (THDR), a value expressed as a ratio of 1, which is obtained from the THD_I as a ratio of one according to Equation (15):

$$THDR = 1 - THD_I, \tag{15}$$

Although the THDR factor was incorporated into the Q_{RE} formulation due to the recognized impact of harmonic distortion on power quality and grid performance, it could not be evaluated in the present study because the required measurements were not available. Harmonic distortion monitoring at the wind turbine level is not commonly implemented in wind farms, and such measurements are typically performed at the wind farm or substation level. Consequently, the dataset analyzed in this work did not provide the information required to calculate the THDR. Therefore, for the purposes of this study, the THDR was set equal to 1, ensuring that the absence of harmonic distortion data did not influence the resulting KPI values. Nevertheless, the THDR term has been retained in the proposed Q_{RE} formulation because of its relevance as a power quality indicator and to enable its application in future studies where harmonic distortion measurements are available.

Figure 5 shows the OEE model applied to wind energy turbines.

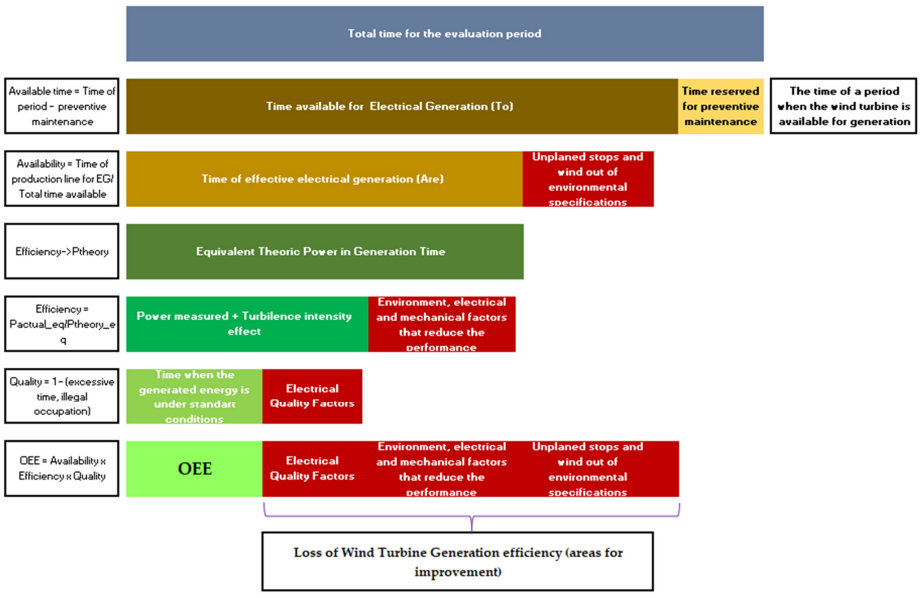


Figure 5. Chart of the OEE applied to wind energy turbines, adapted from Gil Gallego et al. [20], based on the OEE model originally proposed by Nakajima [5].

2.2. Data Acquisition and Processing

2.2.1. Data Acquisition Architecture

The validation of the proposed OEE_{RE} methodology was carried out using operational data acquired from a utility-scale wind farm. Data collection was based on a hybrid architecture integrating the existing supervisory control and data acquisition (SCADA) system with an additional datalogger installed at the wind farm substation.

The datalogger was directly connected to the SCADA infrastructure and configured to collect the electrical and operational variables required for the computation of the OEE_{RE} indicators. This setup enabled the acquisition of synchronized time-series data with a sampling rate of approximately 1 Hz, providing sufficient temporal resolution to capture short-term operational dynamics while remaining compatible with standard industrial monitoring systems. A schematic representation of the data acquisition architecture is provided in Figure 6.

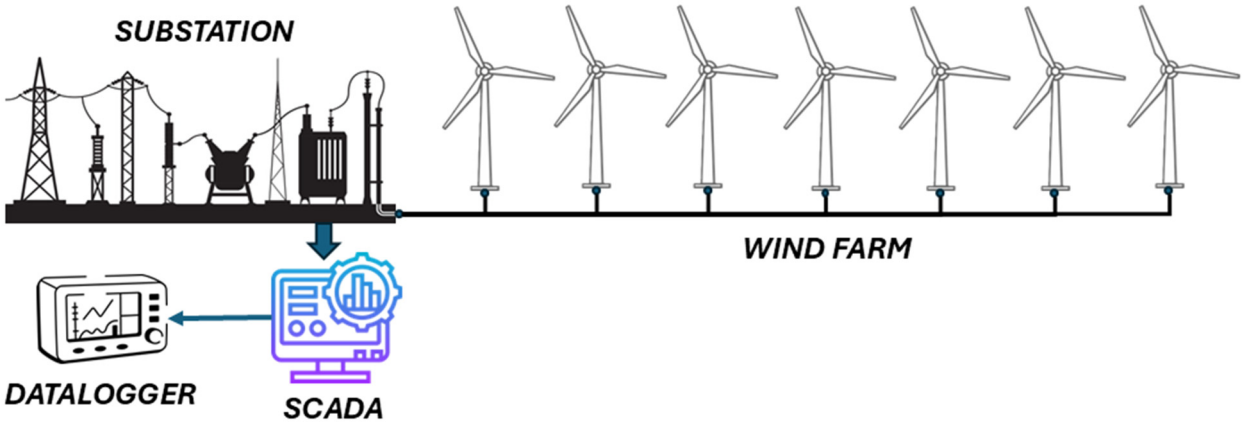


Figure 6. Data acquisition architecture based on SCADA and substation datalogger integration.

A total of seven wind turbines (WTs) were monitored during the 2023 operating year, forming the dataset used for the computation and analysis of the OEE_{RE} indicator and its associated components. The processed dataset was subsequently used to calculate the availability (A_{RE}), performance (P_{RE}), and quality (Q_{RE}) indicators, as well as the aggregated OEE_{RE} value. This implementation demonstrates that the proposed methodology can be deployed using standard SCADA infrastructure complemented by a substation-level datalogger, without requiring additional sensors at turbine level or significant modifications to the existing monitoring system.

2.2.2. Data Processing

The processing of the acquired data was performed offline, as the present work corresponds to a research study focused on the validation and analysis of the proposed OEE_{RE} methodology. Nevertheless, it is worth noting that the deployed data acquisition device (substation-level datalogger) is technically capable of performing real-time computation of the OEE_{RE} indicators, which enables future implementations oriented toward online monitoring and operational decision making.

The OEE_{RE} components were computed using 10 min data windows throughout the entire measurement period. The selection of this aggregation interval is consistent with standard wind energy industry practices and the temporal resolution commonly employed in SCADA systems and IEC-compliant performance assessment methodologies [12]. Averaging operational measurements over 10 min periods reduces the impact of short-term stochastic variations in wind speed and power output, yielding statistically representative

operating states while retaining sufficient sensitivity to detect changes in turbine performance. Therefore, this temporal resolution provides an effective compromise between data granularity, statistical reliability, and computational efficiency. For each time window, the availability (A_{RE}), performance (P_{RE}), and quality (Q_{RE}) indicators were calculated from the corresponding operational measurements.

The calculation of the performance indicator (P_{RE}) requires an accurate estimation of air density, as this parameter directly affects the expected power output derived from the wind turbine power curve. Since air density is not typically measured directly in commercial wind farms, an indirect estimation approach was adopted. Air density was calculated as a function of ambient temperature, barometric pressure, and relative humidity.

Ambient temperature measurements were obtained directly from the wind turbine SCADA system, whereas barometric pressure was estimated from the site elevation above mean sea level using the International Standard Atmosphere (ISA) formulation (16):

$$p = 101325\left(1 - \frac{0.0065h}{288.15}\right)^{5.25588}, \quad (16)$$

where p is the atmospheric pressure (Pa), and h is the elevation above mean sea level (m). Since direct pressure measurements were not available, the ISA model was used to provide a consistent estimate of local atmospheric pressure. However, actual pressure conditions may deviate from ISA-derived values due to local weather variability and synoptic atmospheric systems. Typical pressure deviations associated with anticyclonic and cyclonic conditions can reach approximately ±10 to ±20 hPa, potentially introducing an uncertainty in the order of 1–2% in the estimated air density.

Relative humidity was not directly available from on-site measurements and was, therefore, estimated through an independent analysis of historical humidity data corresponding to the geographical coordinates of the wind farm, obtained from open-access meteorological data sources [21]. This analysis allowed the characterization of the annual trend of relative humidity (see Figure 7), which was subsequently incorporated into the air density estimation used for P_{RE} computation.

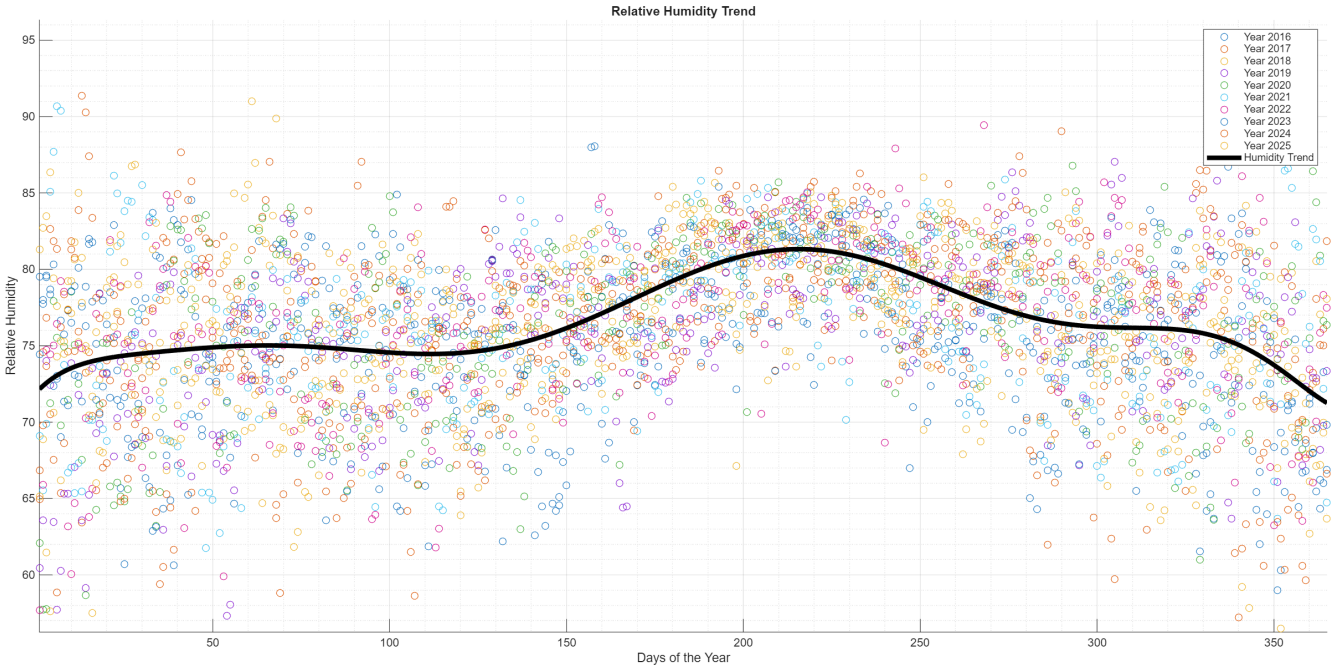


Figure 7. Annual trend of relative humidity at the wind farm location. The trend line is shown in black.

A sensitivity analysis of the input variables used for air density estimation is presented in Table 2. The results indicate that atmospheric pressure variability represents the primary source of uncertainty, followed by temperature measurements, while the contribution of relative humidity is comparatively minor. Consequently, the overall uncertainty associated with the estimated air density is expected to remain within approximately 1–2%. This uncertainty is considered acceptable for the purposes of the present performance assessment, given the use of publicly available meteorological data and the long-term nature of the analysis.

Table 2. Estimated uncertainties associated with air density calculation inputs.

Var	Data Source	Typical Uncertainly	Estimated Impact on Air Density
Temperature	Wind Turbine SCADA	±1–2 °C	±0.3–0.7%
Relative humidity	NASA POWER (RH2M, MERRA-2)	±10% RH	<±0.3%
Atmospheric pressure	ISA model based on site elevation	±10–20 hPa	±1–2%
Air density	Calculated	-	≅±1–2%

This data-processing approach enables a more realistic estimation of air density compared with simplified assumptions based solely on standard atmospheric conditions, thereby improving the accuracy of the performance indicator without requiring additional sensors or modifications to the existing wind farm infrastructure.

In addition to the air density correction, an additional adjustment based on turbulence intensity (TI) was applied in the performance indicator (P_{RE}) calculation. This correction accounts for the influence of turbulence on wind turbine power output, which is not explicitly captured by the standard manufacturer's power curve.

The compensated power output aims to reduce the systematic power deviations induced by variations in turbulence intensity, thereby improving the consistency of the correlation obtained when comparing the measured power production with the equivalent power derived from the reference power curve. This correction is particularly relevant in operating conditions where turbulence effects introduce bias in performance evaluation despite similar wind speed conditions.

The correction coefficient k was determined empirically from the analysis of the measured data over the entire monitoring period. For this purpose, the relationship between turbulence intensity and measured power output was analyzed, and a linear fit was used to characterize the average power deviation associated with variations in turbulence intensity, as illustrated in Figure 8. The calibration process was conducted separately for each wind turbine in order to account for turbine-specific responses to turbulence effects.

While air-density uncertainty was estimated to remain within approximately 1–2%, the uncertainty associated with turbulence intensity compensation is larger due to the significant dispersion observed in the calibration data. Consequently, the turbulence correction should be regarded as a first-order approximation intended to reduce systematic bias rather than to completely remove turbulence-related effects.

Overall, the sensitivity analysis indicates that the P_{RE} indicator is most strongly affected by wind speed uncertainty due to the cubic relationship between wind speed and power production. Air density uncertainty has a comparatively limited impact, estimated to remain within approximately ±2%. The turbulence intensity correction introduces additional uncertainty because of the dispersion observed in the calibration data; however, it contributes to reducing systematic deviations between measured and theoretical power production. Consequently, the uncertainty associated with P_{RE} is expected to be dominated by wind speed measurements, particularly under low-wind-speed operating conditions,

where small measurement errors may lead to large relative deviations in the calculated performance indicator.

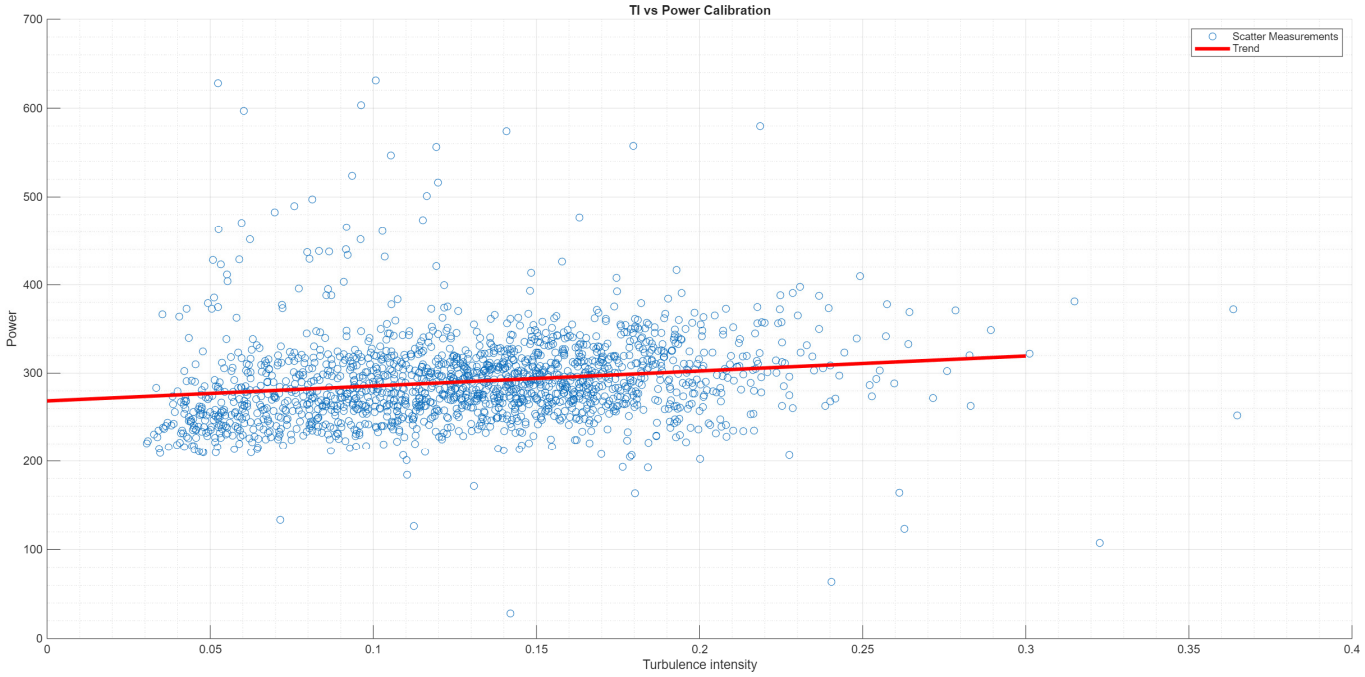


Figure 8. Calibration of the turbulence intensity correction at a fixed-wind-speed operating point.

3. Results

3.1. Annual OEE_{RE} KPI Summary

Table 3 summarizes the annual values of the OEE_{RE} indicator and its associated metrics—availability, performance and quality—calculated from the available operational data. Due to data acquisition issues, measurements were not available for several months of the analyzed period; only days with valid data were considered in the computation.

Table 3. ARE results table. Period: 2023.

Indicator		WT1	WT2	WT3	WT4	WT5	WT6	WT7
Analyzed days		209	209	208	209	210	210	210
Wind-in-range ratio		0.87	0.87	0.87	0.88	0.87	0.87	0.87
Generated energy		2346 GWh	2115 GWh	2286 GWh	2432 GWh	2182 GWh	2210 GWh	2424 GWh
Mean OEE_{RE}		0.651	0.645	0.837	0.676	0.630	0.640	0.689
Mean availability	A_{RE}	0.978	0.973	1.000	0.987	0.982	0.995	0.997
Mean performance	P_{RE}	0.869	0.860	1.216	0.930	0.875	0.873	0.951
Mean quality	Q_{RE}	0.686	0.675	0.796	0.684	0.668	0.675	0.694

Table 3 summarizes the annual KPIs associated with the proposed OEE_{RE} indicator for seven wind turbines (WT1–WT7) during the 2023 period, calculated using the available days with valid operational data. For each wind turbine, the number of analyzed days, wind-in-range ratio, and total generated energy are reported, together with the mean OEE_{RE} value and its corresponding components: availability (A_{RE}), performance (P_{RE}), and quality (Q_{RE}).

As observed, WT3, WT4, and WT7 exhibit, in general, better operational performance compared with the remaining wind turbines. This behavior is reflected by higher mean OEE_{RE} values and more favorable contributions from the availability, performance and

quality metrics. A potential contributing factor to this improved performance may be the closer proximity of these wind turbines to the coastline (see Figure 9), where more stable wind conditions and reduced terrain-induced disturbances are typically expected. However, this aspect has not been explicitly analyzed in the present study and is, therefore, considered a qualitative interpretation rather than a demonstrated causal relationship.

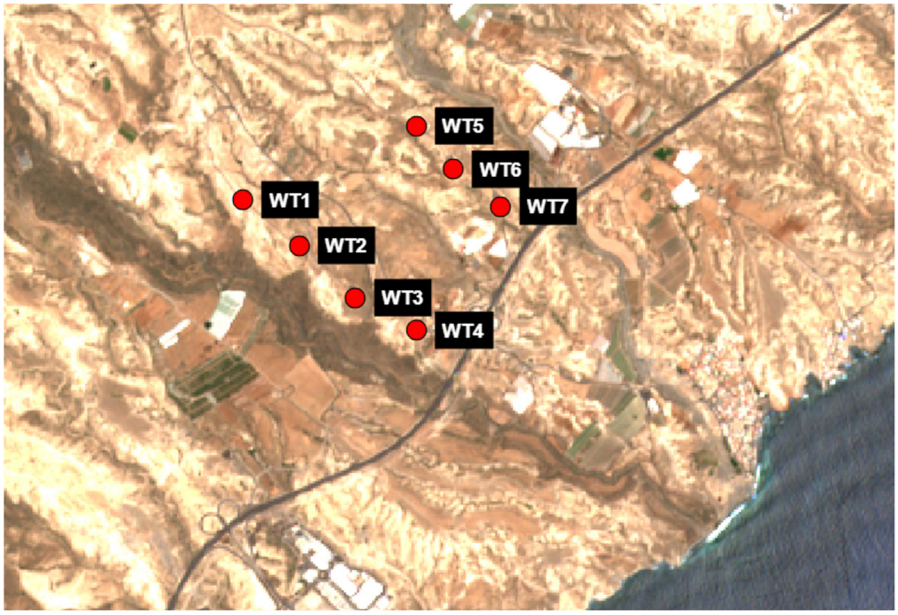


Figure 9. Spatial distribution of the analyzed wind turbines within the wind farm. Sentinel-2A MSI Level-2A image acquired on 25 June 2026, provided by ESA under the Copernicus Program; annotations added by the author [22].

3.2. Behavior of the Availability Indicator A_{RE}

The mean availability values (A_{RE}) are consistently close to unity for all analyzed wind turbines. This behavior is expected, as availability within the proposed OEE_{RE} framework is evaluated exclusively during periods when the wind speed remains within the operational limits of the turbines. Under these conditions, a value of A_{RE} close to 1 represents the normal operating behavior. Any deviation from this reference level can, therefore, be associated with unplanned stoppages or maintenance activities that were not scheduled during low-wind periods, resulting in a loss of potential energy production. As a result, availability is not expected a priori to be the main limiting factor for OEE_{RE} in the analyzed case, while performance and quality play a more relevant role in the observed efficiency differences.

3.3. Behavior of the Performance Indicator P_{RE}

The performance indicator (P_{RE}) exhibits greater variability than A_{RE} across analyzed wind turbines, as shown in Table 3. This behavior is expected because P_{RE} is directly derived from the ratio between the measured power output and the reference power curve under the corresponding wind conditions. Consequently, P_{RE} provides a direct measurement of the turbine's ability to convert the available wind resource into electrical energy and represents one of the most influential components within the OEE_{RE} formulation.

WT3 exhibited a mean performance value above unity (P_{RE} = 1.216), indicating that the measured energy production exceeded the energy predicted by the reference model. This result should not be interpreted as an efficiency greater than 100%, but rather because of the uncertainty associated with the reference power curve, wind speed measurements, air density estimation, and the inherent variability in wind turbine operation. Such effects are particularly pronounced within the partial-load region of the power curve, where small

deviations in wind speed can produce large relative differences between expected and measured power output. Therefore, caution should be exercised when interpreting P_{RE} values obtained at wind speeds below approximately 5 m/s, where the indicator exhibits reduced robustness due to the increased relative effect of uncertainty.

Figure 10 illustrates the relationship between wind speed and P_{RE}. A substantial dispersion of performance values can be observed at low wind speeds (approximately 3–5 m/s), including values above unity. In this operating region, the turbine generates relatively low power, and the reference power curve exhibits greater uncertainty, causing small absolute errors to be amplified when expressed as a relative indicator. As wind speed increases, P_{RE} progressively converges toward unity and displays reduced variability, indicating a more stable and predictable operating regime. Therefore, the high dispersion observed at low wind speeds should be regarded as an intrinsic characteristic of percentage-based performance indicators rather than evidence of abnormal turbine behavior.

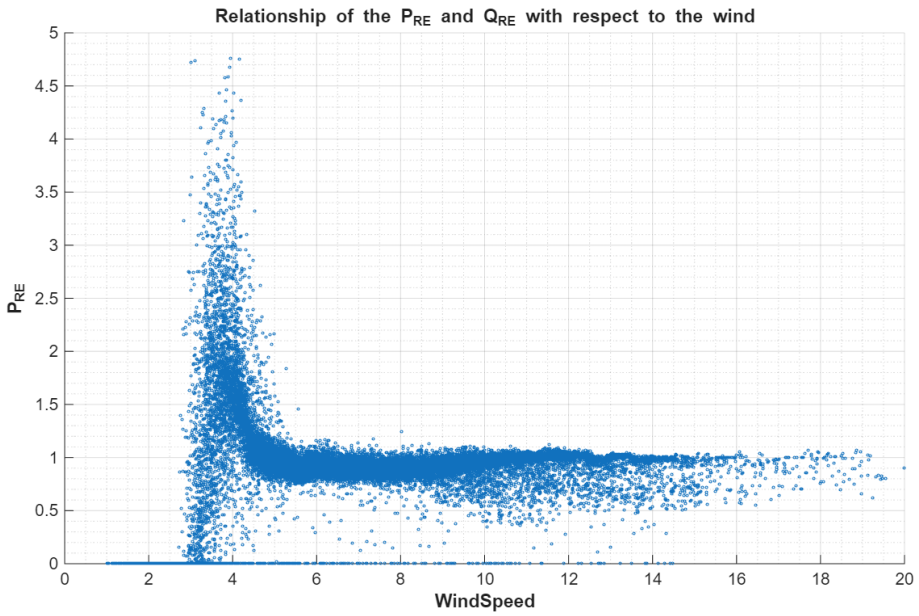


Figure 10. Performance indicator P_{RE} as a function of wind speed.

Overall, the results confirm that P_{RE} is strongly dependent on wind speed conditions and that its interpretation should primarily focus on the operating range that contributes most significantly to annual energy production.

The uncertainty associated with air density estimation, estimated to be in the order of 1–2%, may also contribute to the occurrence of performance values slightly above unity, particularly within the low-wind-speed operating region.

3.4. Behavior of the Quality Indicator Q_{RE}

Figure 11 shows the relationship between wind speed and the quality indicator Q_{RE} for a representative wind turbine. Although several factors may contribute to quality-related losses within the OEE_{RE} framework, the cosine of the phase angle (cos φ) emerges as the dominant influencing parameter in the analyzed case.

The results reveal a strong dependence of Q_{RE} on wind speed conditions. At low wind speeds, Q_{RE} values are significantly reduced and exhibit high variability, reflecting suboptimal electrical operating conditions and reduced power quality performance at low load levels. As wind speed increases, Q_{RE} rises rapidly and converges toward values close to unity, indicating improved electrical behavior and a more efficient conversion of generated power.

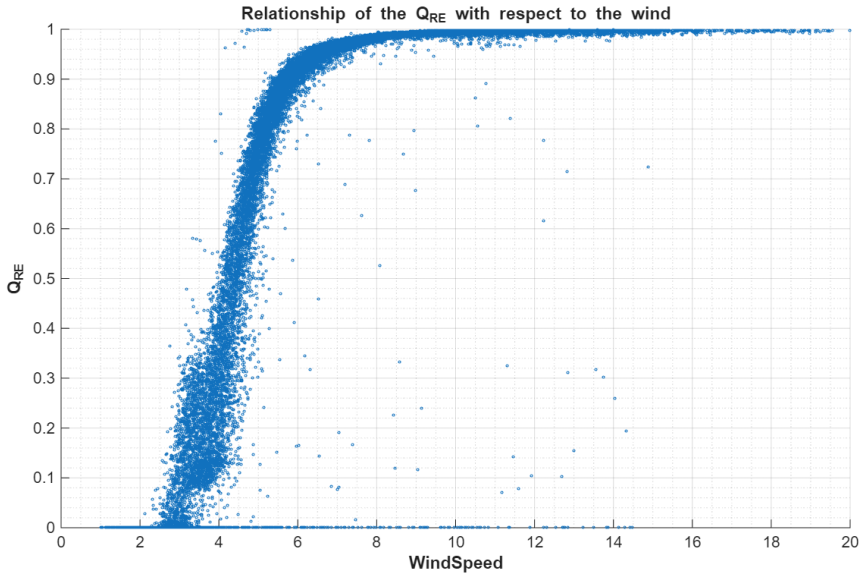


Figure 11. Quality indicator Q_{RE} as a function of wind speed.

Once the turbine operates within its nominal wind speed range, Q_{RE} remains close to unity with limited dispersion, suggesting that quality-related losses become negligible under normal operating conditions. This behavior confirms that quality losses are primarily concentrated at low wind speeds and have a limited impact on overall energy production, while still contributing to the variability in OEE_{RE} across different operating regimes.

4. Discussion

4.1. Interpretation of OEE_{RE} Components

The results obtained in this study provide relevant insights into the applicability and interpretability of the adapted OEE_{RE} indicator for wind energy systems. By analyzing availability, performance, and quality as separate but interrelated components, the proposed framework enables a detailed understanding of the factors that drive efficiency differences among wind turbines operating under similar environmental conditions.

From the availability perspective, the consistently high A_{RE} values observed across all analyzed wind turbines indicate that technical availability is not, a priori, the main limiting factor of OEE_{RE} in the analyzed case. This behavior is consistent with the proposed definition of availability, which is evaluated exclusively under wind speed conditions within the operational range of the turbines. Under this formulation, deviations from ideal availability values are primarily associated with unplanned stoppages or maintenance activities occurring during potentially productive periods, rather than with the wind resource itself.

In contrast, performance (P_{RE}) emerges as a dominant contributor to the variability in the overall OEE_{RE} values. The strong dependence of P_{RE} on wind speed conditions, together with its direct formulation based on the comparison with the reference power curve, makes performance particularly sensitive to aerodynamic effects, wake interactions, control strategies, and site-specific characteristics. The observed dispersion of P_{RE} at low wind speeds can be partially attributed to the percentage-based nature of the indicator, where small absolute deviations in power output are magnified in relative terms in regions of low energy production. Furthermore, uncertainties associated with wind speed measurements, air density estimation, and reference power curve modeling have a proportionally greater effect within the partial-load operating region, particularly in wind farms characterized by predominantly low-wind-speed conditions. Future research could, therefore, investigate the introduction

of a weighting or attenuation factor as a function of the turbine operating range or energy contribution, with the aim of reducing the influence of uncertainty under low-wind-speed conditions and improving the robustness of the P_{RE} indicator. Consequently, the interpretation of performance-related losses should focus primarily on the main operational wind speed range, where P_{RE} has the greatest impact on total energy generation.

Quality-related effects, captured through the Q_{RE} indicator, further complement the performance analysis by accounting for losses that are not directly associated with turbine availability or aerodynamic efficiency. In the analyzed case, the cosine of the phase angle ($\cos \varphi$) appears as the most influential contributor to quality losses. The strong dependence of Q_{RE} on wind speed highlights how electrical operating conditions and load levels affect power quality, particularly at low wind speeds, while quality-related losses become negligible once the turbine operates under nominal conditions. This behavior confirms that Q_{RE} provides valuable complementary information to performance metrics, especially when assessing efficiency losses outside the primary energy-producing regime.

Additionally, the observed differences in OEE_{RE} among wind turbines suggest that site-related factors, such as relative proximity to the coastline, may influence overall performance through more stable wind conditions and reduced terrain-induced disturbances. While this aspect has not been quantitatively assessed in the present study, the spatial distribution of the analyzed turbines supports a qualitative interpretation of location-dependent effects, emphasizing the importance of contextual information when evaluating OEE_{RE} values.

Overall, the proposed OEE_{RE} framework proves effective in capturing multiple dimensions of wind turbine efficiency within a single, interpretable KPI. Unlike traditional energy-based indicators, OEE_{RE} enables the identification of performance and quality losses that may otherwise remain concealed, supporting a more comprehensive assessment of wind energy assets.

Finally, this study is subject to several limitations. Data gaps were present due to data acquisition system failures, and the analysis focused on a limited number of turbines within a single wind farm. Future work will address these limitations by incorporating longer monitoring periods, additional wind farms with diverse layouts and terrain conditions, and a more detailed investigation of wake effects, curtailment strategies, and grid interaction phenomena. Furthermore, the integration of energy-weighted performance metrics may help reduce the relative distortion observed in low-wind-speed regimes.

Despite the robustness of the proposed OEE_{RE} framework, some aspects merit further investigation. As discussed in the performance and quality analyses, percentage-based indicators such as P_{RE} and Q_{RE} exhibit increased variability at low wind speeds, where absolute energy production is limited and small deviations are amplified in relative terms. Although these operating conditions have a minor influence on the total energy yield, they may affect the interpretation of efficiency metrics. Future work could explore techniques to mitigate these effects, such as energy-weighted formulations, wind speed binning approaches, or operating-regime-dependent weighting factors, with the aim of enhancing the robustness of OEE_{RE} while preserving its interpretability and applicability to renewable energy systems.

4.2. Comparison with Existing Approaches

The adaptation of OEE to wind energy systems has evolved progressively from conceptual frameworks to operational implementations. Krokoszinski (2003) [7] introduced one of the first OEE-based approaches for wind farms, proposing the TotalOEE concept to relate operational losses with energy production and revenue. However, the methodology was primarily intended for farm-level economic assessment and did not rely on turbine-level operational measurements.

Sathler et al. (2020) [23] subsequently validated the application of OEE using operational wind farm data, demonstrating a strong relationship between OEE and productivity. Their approach evaluated performance through deviations from the best observed power output in each wind speed range but did not explicitly account for air density or turbulence corrections. Furthermore, the quality factor was assumed to be equal to unity because suitable measurements were not available.

A later review by Sathler et al. (2023) [9] provided a comprehensive classification of wind energy losses according to the OEE framework and highlighted the relevance of environmental variables such as air density, turbulence intensity, wake effects, and grid-related constraints. Nevertheless, the work remained primarily conceptual and did not propose a complete SCADA-based implementation methodology. The main characteristics of the reviewed approaches and their comparison with the proposed OEE_{RE} methodology are summarized in Table 4.

Table 4. Comparison of OEE-based methodologies reported in renewable energy systems.

Feature	Krokoszinski (2003) [7]	Sathler et al. (2020) [23]	Sathler et al. (2023) [9]	Bella et al. (2021) [8]	Proposed OEE_{RE}
Renewable energy	Wind	Wind	Wind	PV	Wind
OEE framework	✓	✓	✓	✓	✓
Practical implementation	Partial	✓	✓	✓	✓
Real operational data	✗	✓	✗	✓	✓
SCADA-based analysis	✗	✓	✗	✗	✓
Turbine-level assessment	✗	✓	Partial	-	✓
Availability factor	✓	✓	✓	Use operational availability (OA)	✓
Performance factor	✓	✓	✓	Use performance rate (Tp)	✓
Quality factor	Partial	✗ Q = 1	Conceptual	✓	✓
Manufacturer power curve	✓	✗	✓	✓	✓
Air density correction	✗	Mentioned	✓	-	✓
Turbulence correction	✗	✗	✗ Recommended	-	✓

Note: ✓ indicates that the feature is included; ✗ indicates that the feature is not included; – indicates that the feature is not applicable or was not reported; *Partial* indicates partial implementation or consideration.

Compared with these approaches, the OEE_{RE} methodology proposed in this work focuses on turbine-level assessment using variables available in standard industrial SCADA systems. In addition, the performance indicator incorporates manufacturer power curve normalization according to IEC 61400-12 recommendations, including air density correction and turbulence intensity compensation. Finally, quality is evaluated through electrical parameters directly available at turbine level, enabling practical implementation without requiring additional instrumentation. Therefore, OEE_{RE} provides a bridge between previous conceptual adaptations and a deployable methodology compatible with existing wind-farm-monitoring infrastructures.

5. Conclusions

This study proposed and validated the Overall Equipment Effectiveness for Renewable Energy (OEE_{RE}) framework as an adaptation of the traditional OEE methodology to wind energy systems from a wind turbine perspective. The proposed methodology was successfully implemented using operational data collected from seven wind turbines and was specifically

designed to operate with information available from standard wind farm SCADA systems, facilitating its practical adoption without requiring additional instrumentation.

One of the main contributions of this work is the reformulation of the performance indicator (P_{RE}) to better represent the operational reality of wind turbines. Unlike conventional approaches, the proposed methodology incorporates power curve normalization according to IEC 61400-12 recommendations, including both air density correction and turbulence intensity compensation. These corrections reduce the influence of environmental conditions on performance assessment and provide a more realistic representation of turbine behavior under actual operating conditions.

A further contribution of the proposed framework is the enhancement of the quality indicator (Q_{RE}). Traditional adaptations of OEE to renewable energy systems have mainly focused on grid-related incidents and energy delivery constraints. In contrast, the proposed methodology also incorporates the electrical power factor as a quality indicator. This parameter plays a critical role in the efficiency of energy conversion systems, since poor power factor conditions are associated with additional electrical losses, increased thermal stress, and potential long-term equipment degradation. The inclusion of this variable allows Q_{RE} to capture operational inefficiencies that are not adequately reflected by conventional quality assessments.

The application of the methodology demonstrated that availability generally remains high and exhibits limited variability among turbines, whereas performance and quality are the factors that most strongly influence OEE_{RE} values. Consequently, OEE_{RE} provides a more comprehensive representation of wind turbine efficiency than conventional production-based indicators, enabling the identification of operational deviations, hidden performance losses, and differences in turbine behavior that may otherwise remain unnoticed.

From a practical perspective, the proposed indicator constitutes a unified KPI capable of supporting asset benchmarking, anomaly detection, maintenance planning, operational optimization, and future predictive maintenance strategies. Because all required variables are available through standard SCADA systems, the methodology can be readily integrated into existing monitoring infrastructures, making OEE_{RE} a useful tool for renewable-energy asset management.

Future work will focus on validating the proposed OEE_{RE} methodology across a larger number of wind farms operating in different layouts, terrain conditions, and climatic environments. Additional research should investigate the influence of wake effects, curtailment strategies, and grid interaction phenomena on the obtained OEE_{RE} values.

Particular attention should be devoted to further improving the calculation of the performance factor (P_{RE}). Although the proposed formulation incorporates air density correction and turbulence intensity compensation in accordance with IEC 61400-12 recommendations, the analysis revealed that the interpretation of P_{RE} may become less intuitive under low-wind-speed conditions, especially in the vicinity of the turbine cut-in region. In this operating range, small variations in wind speed can result in significant fluctuations in power production, potentially affecting the representativeness of the performance indicator. Future research should, therefore, investigate alternative formulations or additional correction mechanisms capable of providing a more robust and physically meaningful assessment of turbine performance at low wind speeds.

Future developments should also evaluate additional quality-related indicators that may further enhance the characterization of wind turbine operating conditions and their impact on long-term asset performance.

Finally, the integration of OEE_{RE} into real-time monitoring platforms, predictive maintenance frameworks, and digital-twin environments represents a promising direction for improving operational decision making, fault detection, and renewable energy asset management.

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Conflicts of Interest: Óscar Muñoz and Juan Carlos Sánchez were employed by the company TECNALIA. The other authors declare that this research was conducted in the absence of any commercial or financial relationship that could be interpreted as a potential conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

OEE	Overall Equipment Effectiveness
KPI	Key Performance Indicator
OEE_{RE}	Overall Equipment Effectiveness for Renewable Energy
SCADA	Supervisory Control and Data Acquisition
A	OEE Availability
P	OEE Performance
Q	OEE Quality
A_{RE}	OEE Availability of Renewable Energy
P_{RE}	OEE Performance of Renewable Energy
Q_{RE}	OEE Quality of Renewable Energy
PF	Power Factor ($\cos\varphi$)
FVFR	Frequency/Voltage Fault Ratio
GR	Generation Ratio
THDR	Total Harmonic Distortion Ratio
TI	Turbulence Intensity
WT	Wind Turbine

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