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Development of a Digital Twin Framework for Condition Monitoring and Performance Assessment of a Wind Turbine

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Abstract. The paper presents a comprehensive quasi-static digital twin of a utility-scale wind turbine developed in Python. The proposed digital twin framework combines dynamically acquired turbine measurements with static system parameters to reconstruct the steady-state operational behaviour of the wind turbine under real-world conditions. The digital twin integrates historical and real-time operational data to provide dynamic visualization of key performance indicators, enabling continuous insight into turbine behaviour and operational conditions. The model is trained using comprehensive SCADA datasets, including turbine operational data, grid measurements, meteorological observations, and alarm logs, with target variables encompassing the turbine's active power output and efficiency-related performance metrics. Through systematic data processing, filtering, and aggregation, the digital twin provides a representation of expected turbine behaviour across a wide range of operating conditions. The developed digital twin supports performance benchmarking, operational condition assessment, and early detection of deviations that may indicate aerodynamic inefficiencies, control limitations, or emerging component degradation. Its quasi-static formulation ensures computational efficiency and numerical robustness, making it suitable for real-time deployment within wind farm monitoring environments.

The presented approach is fully transparent, reproducible, and modular, allowing straightforward extension toward advanced digital twin functionalities, including condition-based maintenance, performance degradation analysis, and integration with forecasting or control-oriented applications.

Key words. Digital twin, Wind turbine, Power production, Prediction

1. Introduction

The concept of the digital twin (DT) has gained significant attention in recent years as a key enabler of digitalization in energy systems and industrial applications [1]. The design of DTs in the wind energy sector is a case in point, where they are being developed to increase the safety, reliability, and optimal efficiency of turbines by enabling pre-emptive monitoring and maintenance [2], and to support decision making over their design and use, [3, 4].

A digital twin (DT) is a set of virtual information constructs that mimics the structure, context, and behaviour of a natural, engineered, or social system (or system-of-systems). It is dynamically updated with data from its physical twin, has predictive capabilities, and supports value-driven decision-making. The bidirectional interaction between the virtual and the physical is central to the DT. Following this definition, the key elements that comprise a DT include:

i) modelling and simulation to create a virtual representation of a physical counterpart, and

ii) a bidirectional interaction between the virtual and the physical (feedback loop), [5].

While many definitions focus primarily on the intended outcome of twinning, they often underemphasize its nature as an active design process involving deliberate boundary-setting decisions, [6]. In this sense, digital twinning is not merely the mirroring of physical reality in a virtual model, but a purposeful construction shaped by choices regarding which aspects of the physical system are represented, abstracted, or excluded, [7].

In the context of renewable energy systems, and wind turbines in particular, DTs offer a systematic approach to understanding complex interactions between aerodynamic, mechanical, electrical, and control subsystems.

Traditionally, wind turbine (WT) monitoring has relied on supervisory control and data acquisition (SCADA) systems, which provide large volumes of time-series data related to power production, wind conditions, component temperatures, alarms, and electrical quantities. While SCADA-based analysis is widely used for basic performance assessment and fault detection, it is often limited to threshold-based alarms or isolated indicators that do not fully capture the underlying physical mechanisms or cross-domain dependencies. As WTs increase in size and complexity, and as they operate under more variable environmental and grid conditions, these limitations become increasingly pronounced.

DT approaches aim to overcome these challenges by combining physics-based knowledge, data-driven models, and operational data within a unified framework. In wind energy applications, DTs have been explored for purposes such as wake effect [8], detection of aerodynamic degradation [9], analysis of yaw and pitch system performance [10], assessment of drivetrain and generator health [11, 12], and evaluation of grid-related impacts, [13].

Building upon these developments, this paper introduces a quasi-static, data-driven DT of a utility-scale WT, developed in Python and based exclusively on SCADA data streams (set of operational, grid, meteorological and state notifications), enabling continuous performance reconstruction, condition monitoring, and operational diagnostics in near real time.

The subsequent sections of the paper describe the architecture of the proposed DT, the employed performance and condition indicators, and the insights gained from their application to a real WT case study.

2. Definition of Digital Twin Parameters

A fundamental prerequisite for the development of a consistent, interpretable, and extensible DT is the explicit definition of the parameters that describe both the physical asset and its operational behaviour. In this work, wind turbine's parameters are systematically classified into static and dynamic categories, according to their temporal variability and functional role within the modelling framework, as summarized in Table I.

Static parameters describe the intrinsic characteristics of the WT and remain constant over its operational lifetime or vary only on long time scales. These parameters define the identity, geometry, rated performance, and design constraints of the asset, thereby establishing the structural context of the DT. They include general turbine descriptors, geometric and aerodynamic properties, as well as drivetrain and electrical specifications. Collectively, static parameters define the physical boundaries within which all dynamic processes evolve and provide the reference framework for performance evaluation.

Dynamic parameters represent time-varying quantities that capture the operational state of the turbine and its interaction with the environment and the electrical grid. In this study, dynamic parameters are grouped into three complementary domains.

Electrical variables characterize the turbine–grid interface. Mechanical and operational variables reflect the internal state of the turbine. Environmental variables describe the external driving conditions. This structured parameterization is essential for the DT concept, as it enables a clear separation between asset definition and operational dynamics while supporting the integration of heterogeneous data sources. By explicitly distinguishing static properties from dynamic electrical, mechanical, and environmental states, the proposed framework provides a transparent and physically meaningful foundation for the DT architecture and the performance reconstruction methodology presented in the subsequent sections.

3. Digital Twin Architecture and Methodology

A. DT Architecture

The proposed DT architecture provides an operationally meaningful virtual representation of a utility-scale WT based on a quasi-static, physics-informed approach. Instead of high-fidelity real-time simulation, synchronized SCADA data are mapped to performance indicators that describe the turbine's aerodynamic, mechanical, electrical, and control behaviour.

Table I. – List of static and dynamic parameters

	Wind turbine
	Address/Manufacturer/GPS coord.
Attributes (static parameters)	Turbine Model
	Hub Height (m)
	Rotor Diameter (m)
	Rated Power (kW or MW)
	Generator type
	Cut in speed (m/s)
	Cut out speed (m/s)
	Speed at achieving rated power (m/s)
	Survival speed (m/s)
	Control type
	Rated rotor speed (rpm)
	Voltage (V)
	Weight tower-nacelle (kg)
	Power curve
	Gearbox type
	Number of stages
	Gearbox ratio
	Noise Level (dB)
	Commissioning Year
	Performance decline (%/year)
Electrical variables (dynamic parameters)	AC Voltage (V)
	AC Current (A)
	Frequency (Hz)
	Active Power (kW/MW)
	Reactive Power (kVAr)
	Power Factor (cosφ)
	Active Energy (kWh/MWh) per WT over time
	Reactive Energy (kVArh)
Mechanical / Operational Variables (dynamic parameters)	Rotor speed (RPM)
	Generator speed (RPM)
	Main shaft speed (RPM)
	Blade pitch angle
	Yaw angle
	Acoustic noise
	Brake status (on/off)
	Tower Vibration Frequency
Environmental Variables (dynamic parameters)	Wind speed (m/s) measured at turbine hub height
	Wind direction measured at turbine height (°)
	Air Temperature (°C) measured at nacelle or nearby sensor
	Relative humidity
	Atmospheric Pressure (hPa) nacelle sensor or local station
	Turbulence intensity

For better understanding, a block diagram of the developed DT architecture is given in Figure 1. The architecture follows a unidirectional data flow from the physical turbine to the digital model, reflecting industrial practice where DTs are primarily used for monitoring and decision support. Measurements from turbine-mounted sensors are aggregated by the SCADA system and transferred to the digital layer. Three time-aligned data streams are considered: operational, meteorological, and grid-related data, supplemented by alarm and event logs.

Within the digital layer, data are synchronized, filtered, and operating states are selected. Non-representative conditions such as start-up, shutdown, curtailment, or fault states are identified using alarm information and treated separately. The resulting dataset captures the intrinsic turbine behaviour under normal operation.

Performance reconstruction forms the core of the DT, combining physics-informed analytical models with data-driven indicators. Aerodynamic, mechanical, and electrical subsystems are evaluated through quasi-static metrics that capture dominant physical dependencies and enable the detection of degradation, misconfiguration, or abnormal operation. A monitoring and diagnostic layer integrates these indicators with historical trends and alarms, enabling condition-aware interpretation of turbine performance.

The DT is implemented in a modular Python-based framework, ensuring transparency, reproducibility, and extensibility for both operational use and further development.

B. Data Sources and Acquisition

The DT relies exclusively on data obtained from the turbine's SCADA system, ensuring applicability without

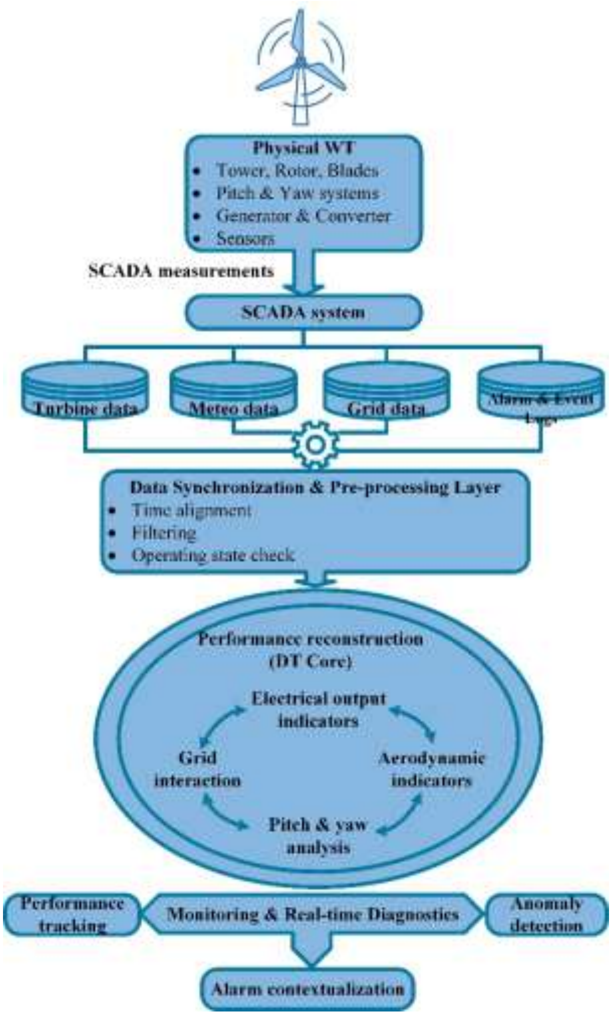

Fig. 1. Conceptual architecture of the proposed DT for a utility-scale WT, illustrating the data flow from SCADA-based measurements to performance reconstruction and diagnostic monitoring.

access to proprietary manufacturer models or high-fidelity simulations. Three primary data categories are considered:

- Turbine operational data, including active and reactive power output, rotor speed, nacelle position, pitch angles of individual blades, generator and converter electrical quantities, and internal status signals.
- Meteorological data, comprising wind speed and wind direction measurements relevant to turbine operation.
- Grid and alarm data, including phase voltages and currents, power factor, and alarm and event logs generated by the turbine control system.

These one-year data streams are time-stamped and sampled at 10-minute resolution, enabling consistent temporal alignment across physical subsystems.

C. Physics-Informed Performance Reconstruction

Aerodynamic performance is assessed through the reconstruction of empirical power curves and the evaluation of the turbine's aerodynamic efficiency using the power coefficient. By relating electrical power output to wind conditions and rotor geometry, the DT enables continuous tracking of performance deviations that may indicate blade degradation, suboptimal pitch settings, or control limitations.

The behaviour of the pitch system is analysed by examining the relative positioning of individual blade pitch angles. Asymmetries between blades are interpreted as potential indicators of mechanical degradation or lubrication-related issues within the pitch actuation system. Additionally, the interdependence between wind speed, pitch angle, and power output is explored to assess control performance under varying operating conditions.

Yaw system performance is evaluated by comparing the nacelle orientation with the prevailing wind direction, allowing the quantification of yaw misalignment. The resulting yaw error is further linked to expected production losses using established analytical relationships, providing insight into nacelle positioning accuracy and the condition of yaw drives or wind direction sensors.

Electrical and grid-related behaviour is reconstructed through the analysis of active and reactive power characteristics, power factor variation with output power, and phase current and voltage imbalances. These indicators support the assessment of generator and converter health, as well as the identification of grid-induced disturbances affecting turbine operation.

D. Diagnostic and Monitoring Functions

By integrating aerodynamic, mechanical, electrical, and control-related indicators within a unified framework, the DT enables continuous monitoring and diagnostic interpretation of turbine behaviour. Deviations between reconstructed performance indicators and expected operating patterns are used to identify potential anomalies and to support condition assessment across subsystems. Alarm information is incorporated as an integral part of the DT, allowing performance deviations to be contextualized with respect to operational constraints, safety interventions, maintenance activities, or grid-related events.

E. Implementation Considerations and Extensibility

The DT is implemented in a modular Python-based framework, facilitating transparency, reproducibility, and extensibility. The chosen structure allows additional performance indicators and diagnostic modules to be incorporated with minimal restructuring, such as turbulence intensity estimation, advanced imbalance analysis, or degradation trend modelling.
The computational efficiency of the proposed quasi-static approach makes it suitable for real-time monitoring and for deployment in wind farm operational environments. At the same time, the framework provides a solid foundation for future extensions towards predictive analytics, control-oriented DTs, and more advanced condition-based maintenance applications.

4. Mathematical Model

In this paper, the approach proposed in [14] is used as a foundation for developing the mathematical model of the DT. The WTDT is based on a physics-informed formulation that enables the estimation of key operational parameters. The generated electrical power is calculated by model based on Weibull's parameters:

$$\left.\begin{array}{ll} P_{el}=0 & (for\, v<v_{cut\,in}) \\ P_{el}=a+bv^k & (for\, v_{cut\,in}\le v\le v_n) \\ P_{el}=P_{el,n} & (for\, v_n<v\le v_{cut\,out}) \\ P_{el}=0 & (for\, v>v_{cut\,out}) \end{array}\right\} \quad (1)$$

where coefficients *a* and *b* are calculated as:

$$a=\frac{P_{el,n}v_c^k}{v_c^k-v_n^k} \text{ and } b=\frac{P_{el,n}}{v_n^k-v_c^k} \quad (2)$$

k is the Weibull shape parameter, *c* (m/s) is the Weibull scale parameter The power coefficient is computed by:

$$C_p=\frac{P_{el}(t)}{\frac{1}{2}\rho(t)Av(t)^3} \quad (3)$$

where P_{el}(kW) is the measured electrical power output, *A* (m^2) is the rotor swept area, *v* (m/s) is the wind speed measured at the turbine nacelle and *ρ* (kg/m^3) is air density, calculated by:

$$\rho(H)=\frac{p(H)}{R\cdot T(H)} \quad (4)$$

since air density depends on height above ground - H [m], temperature-*T* (K), pressure-*p* (Pa) and *R*=287 (J/kg·K)-gas constant.
While the mathematical expressions are standard, the DT's added value emerges from their integration with real SCADA data, operational constraints, and diagnostic logic implemented at the code level.

5. Results and Discussion

The proposed DT is validated using operational data from a utility-scale onshore WT with an installed capacity of 2.3 MW.

A. Power Curve Reconstruction and Performance Consistency

Figure 2 illustrates the reconstructed power curve obtained from the DT, combining scatter plots of measured active power with wind-speed-binned mean values. The results show a clear and physically consistent relationship between wind speed and electrical power output, demonstrating that the DT successfully captures the quasi-static operational behaviour of the turbine across its normal operating range.
The use of binning and filtering significantly reduces measurement noise and outliers typically present in raw SCADA data, resulting in a smooth empirical power curve that aligns with expected turbine characteristics. This confirms that the proposed approach can reproduce realistic power performance without reliance on manufacturer-provided power curves or proprietary models, thereby enhancing transparency and reproducibility. Variations in turbulence intensity, air density, yaw misalignment, and control actions lead to power outputs that deviate from the idealized curve, resulting in point clustering and stratification within narrow wind speed intervals.

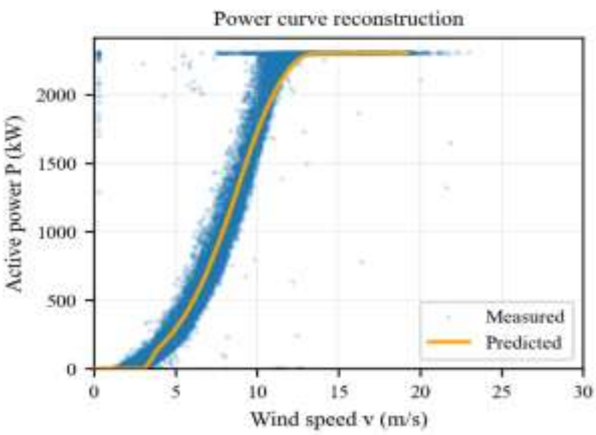

Fig.2. Reference power curve provided by the manufacturer and measured active power output.

B. Power Coefficient Analysis and Aerodynamic Performance

The calculated power coefficient (C_p) as a function of wind speed is presented in Figure 3. The empirical C_p curve exhibits a well-defined operational envelope, with values remaining within physically plausible limits. Deviations and dispersion observed in the C_p scatter reflect the influence of operational conditions, control actions, and environmental variability.
Importantly, the C_p - based representation enables a more physically interpretable assessment of turbine performance compared to power-based indicators alone. Variations in C_p across similar wind-speed bins can indicate aerodynamic degradation mechanisms such as blade surface erosion, contamination, suboptimal pitch settings, or control

constraints. This highlights the suitability of the DT for performance benchmarking and early-stage anomaly detection.

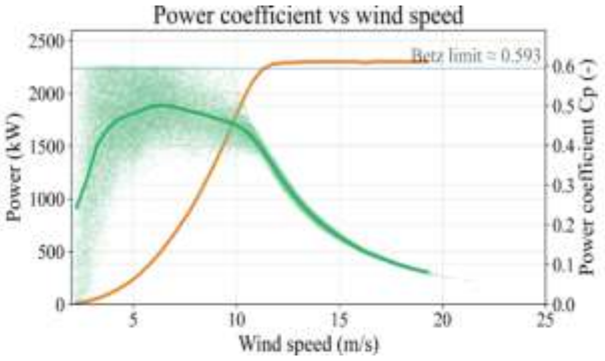

Fig.3. Empirical C_p curve obtained from the DT, illustrating turbine aerodynamic efficiency under varying wind conditions.

The pronounced variability of the power coefficient in the 3–9 m/s wind speed range corresponds to the partial-load operating region, where the turbine is highly sensitive to wind turbulence, yaw error, and pitch control actions. In this region, small variations in wind speed and control response result in significant changes in aerodynamic efficiency.

C. Pitch System Behaviour and Mechanical Diagnostics

The analysis of blade pitch angles reveals the capability of the DT to detect asymmetries between individual blades. Differences observed between the pitch positions of blades A, B, and C under comparable operating conditions suggest potential mechanical wear or lubrication issues within the pitch actuation system. Such asymmetries are particularly relevant, as they may not always trigger immediate alarms but can lead to efficiency losses and increased mechanical stress over time. The DT therefore provides added diagnostic value by exposing subtle mechanical deviations that are difficult to identify using conventional threshold-based SCADA monitoring.

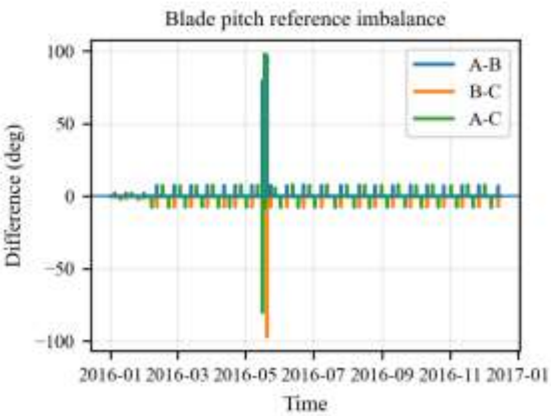

Fig.4. Blade pitch imbalance graph.

The analysis of blade pitch reference asymmetry given in Figure 4 shows that all three blades remain synchronized with negligible deviation during normal operation. Rare extreme differences are isolated events associated with transient operational states and do not indicate persistent mechanical degradation of the pitch system.

D. Yaw Alignment and Directional Performance Losses

Yaw system performance is evaluated by comparing the nacelle yaw position with the measured wind direction, allowing yaw misalignment to be identified and quantified within the DT framework. This analysis supports the assessment of yaw control effectiveness and the detection of potential degradation in yaw drives, control logic, or wind direction sensing, which directly affect energy capture under variable wind conditions.

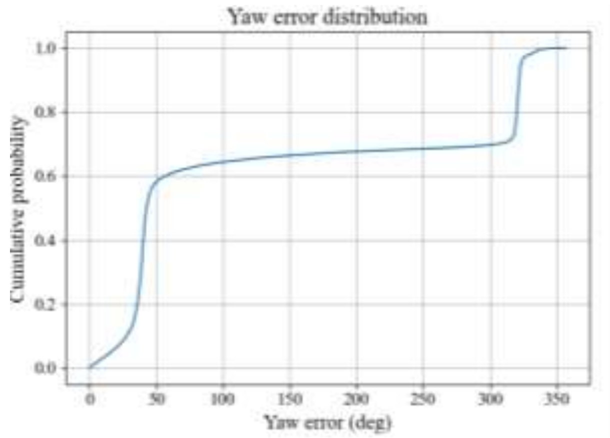

Fig.5. Cumulative distribution function (CDF) of the yaw error angle, calculated as a absolute error between nacelle position and wind direction.

Figure 5 presents the cumulative distribution function (CDF) of the yaw error angle, which quantifies the proportion of operating time during which the turbine operates within a given misalignment threshold. To ensure a physically meaningful interpretation, yaw error is evaluated on a circular basis, accounting for the 0–360° angular domain. This avoids artificial inflation of misalignment values and enables a realistic estimation of yaw-induced performance losses using established aerodynamic relationships.

E. Electrical Behaviour and Grid Interaction

The electrical performance of the turbine is evaluated through the analysis of active and reactive power relationships, power factor variation, and phase imbalance indicators.

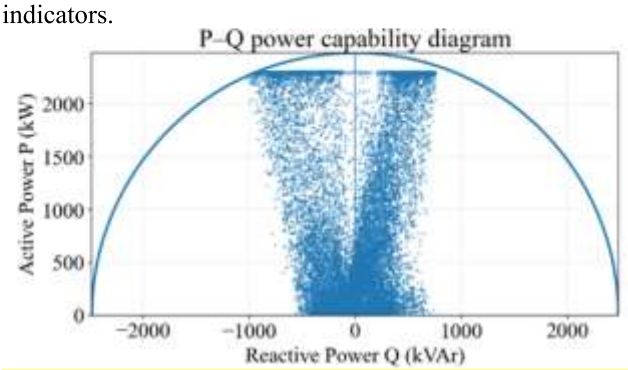

Fig.6. P-Q capability boundary for analysed WT.

The resulting P–Q capability representation (Figure 6), confirms that the turbine operates within expected electrical limits for most of the analysed period. The observed active–reactive power relationship reflects the operating characteristics of an asynchronous generator, which inherently requires reactive power support for magnetization, particularly at lower active power levels.

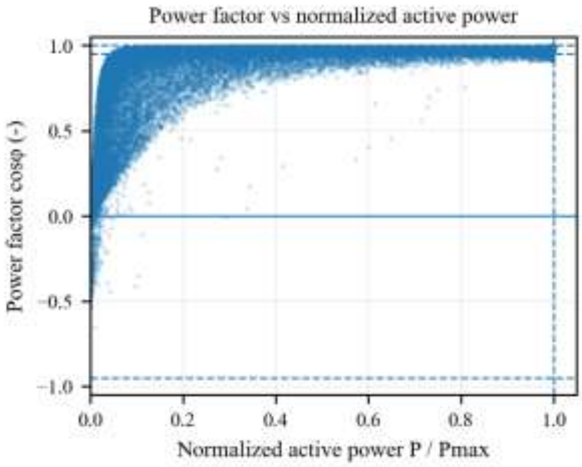

Fig.7. cosφ–P graph for analysed WT.

The combined P–Q capability and cosφ–P analysis (fig. 7.) demonstrates that the wind turbine operates well within its reactive power capability, with near-unity power factor at high load and compliant reactive power control at partial load, indicating healthy generator-converter behavior and no grid-side operational constraints.

6. Conclusion

Overall, the results demonstrate that the proposed DT provides a coherent and physically interpretable representation of WT operation based solely on SCADA data. Unlike conventional monitoring approaches that rely on isolated indicators or alarms, the DT integrates multiple data streams into a unified framework, enabling cross-domain analysis and enhanced situational awareness. The quasi-static nature of the model ensures computational efficiency and robustness, making it suitable for continuous monitoring applications. At the same time, the modular structure of the framework allows for future extensions, including turbulence intensity analysis, degradation modelling, and predictive capabilities. These characteristics position the proposed DT as a practical foundation for advanced WT monitoring and decision-support systems. Additional diagnostic modules, such as turbulence intensity estimation, advanced imbalance analysis, or degradation trend modelling, can be incorporated without altering the fundamental structure of the DT. Unlike many existing DT implementations that rely on proprietary turbine models or high-fidelity simulations, the proposed approach is fully based on standard SCADA data and lightweight analytical formulations, making it transparent, reproducible, and suitable for deployment in operational wind farm environments.

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