energies

Article

Digital Twin as a Virtual Sensor for Wind Turbine Applications

Mahmoud Ibrahim [1,*], Anton Rassõlkin [1], Toomas Vaimann [1], Ants Kallaste [1], Janis Zakis [2], Van Khang Hyunh [3] and Raimondas Pomarnacki [4]

1 Electrical Power Engineering and Mechatronics Department, Tallinn University of Technology, Ehitajate tee 5, 19086 Tallinn, Estonia; anton.rassolkin@taltech.ee (A.R.); toomas.vaimann@taltech.ee (T.V.); ants.kallaste@taltech.ee (A.K.)
2 Institute of Industrial Electronics and Electrical Engineering, Riga Technical University, 12/1 Azenes Street, LV-1048 Riga, Latvia; janis.zakis@rtu.lv
3 Department of Engineering Sciences, University of Agder, Postboks 422, 4604 Kristiansand, Norway; huynh.khang@uia.no
4 Department of Computer Science and Communications Technologies, Vilnius Gediminas Technical University, Saulėtekio al. 11, LT-10223 Vilnius, Lithuania; raimondas.pomarnacki@vilniustech.lt
* Correspondence: mahmoud.mohamed@taltech.ee

Abstract: Digital twins (DTs) have been implemented in various applications, including wind turbine generators (WTGs). They are used to create virtual replicas of physical turbines, which can be used to monitor and optimize their performance. By simulating the behavior of physical turbines in real time, DTs enable operators to predict potential failures and optimize maintenance schedules, resulting in increased reliability, safety, and efficiency. WTGs rely on accurate wind speed measurements for safe and efficient operation. However, physical wind speed sensors are prone to inaccuracies and failures due to environmental factors or inherent issues, resulting in partial or missing measurements that can affect the turbine's performance. This paper proposes a DT-based sensing methodology to overcome these limitations by augmenting the physical sensor platform with virtual sensor arrays. A test bench of a direct drive WTG based on a permanent magnet synchronous generator (PMSG) was prepared, and its mathematical model was derived. MATLAB/Simulink was used to develop the WTG virtual model based on its mathematical model. A data acquisition system (DAS) equipped with an ActiveX server was used to facilitate real-time data exchange between the virtual and physical models. The virtual sensor was then validated and tuned using real sensory data from the physical turbine model. The results from the developed DT model showed the power of the DT as a virtual sensor in estimating wind speed according to the generated power.

Keywords: wind turbine; digital twin; virtual sensor

Citation: Ibrahim, M.; Rassõlkin, A.; Vaimann, T.; Kallaste, A.; Zakis, J.; Hyunh, V.K.; Pomarnacki, R. Digital Twin as a Virtual Sensor for Wind Turbine Applications. *Energies* **2023**, *16*, 6246. https://doi.org/10.3390/en16176246

Academic Editors: Dan-Cristian Popa and Emil Cazacu

Received: 12 July 2023
Revised: 21 August 2023
Accepted: 26 August 2023
Published: 28 August 2023

1. Introduction

The advent of the fourth industrial revolution introduced DT technology to improve the development process. A digital twin (DT) is a virtual replica of a physical object that facilitates real-time simulation and analysis of its performance [1]. DTs are valuable in applications involving wind turbines (WTs) where they can be utilized to monitor the real-time performance of the turbine. This enables engineers to promptly detect and resolve any issues that may arise, thereby enhancing the efficiency and reliability of the WTG while lowering the cost of maintenance and repair [2]. DTs can also be used to optimize the operation of wind turbines by predicting the energy output of the turbine based on the wind conditions. By using the DT to model the turbine's behavior in different wind conditions, engineers can optimize the operation of the turbine to maximize its energy output. This approach can increase the efficiency of the wind turbine and improve its overall performance [3].

In a connected context, wind speed sensors are a critical component of wind farms and are extensively utilized to enable wind energy monitoring, control, and decision support for wind turbines [4]. These sensors measure wind speed, thereby playing a pivotal role in determining the operational performance of wind turbines. The accuracy of these measurements significantly impacts the wind energy capture rate, fatigue load, and service life, ultimately leading to the superior operational efficiency of wind turbines. Wind speed sensors are known to be susceptible to errors, which can have adverse effects on the basic as well as advanced functionalities of wind turbines. This, in turn, can lead to a decrease in the overall performance of wind farms and an increased risk level for the system. Such consequences can range from financial losses to serious safety issues [5]. Therefore, it is imperative to conduct research on online monitoring, identification, and accommodation methods for the sensors to ensure their reliability and accuracy.

In a related context, a virtual sensor is a software-based mechanism that processes data that would otherwise be obtained from physical sensors based on the available information [6]. By observing the readings from different instruments and learning to interpret the relationships between various variables, the virtual sensor functions in a manner that is like a physical sensor. The simulation is designed to imitate the behavior of real-world products and can be used to capture measurements at various locations. The readings obtained from the virtual sensor can supplement the data collected from physical sensors. The primary difference between virtual sensors and estimators is that the latter is a mathematical model that utilizes data to predict future values or events. Virtual sensors can be placed on virtual models anywhere, which is different from the physical world [7]. Digital twins (DTs), which are digital replicas of physical systems or objects, can be used to collect data from virtual sensors. This data can be used to monitor the performance of the DT and predict its behavior. Figure 1 illustrates the general DT structure.

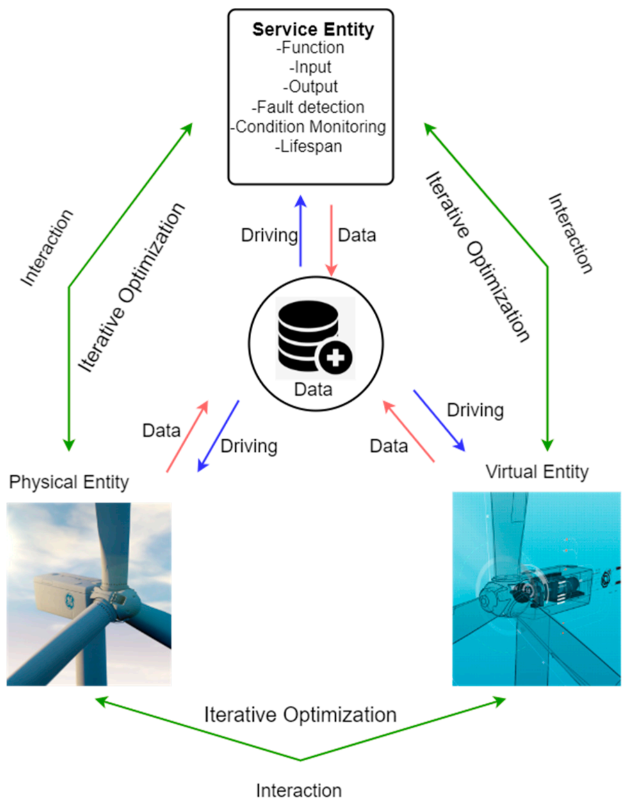

Figure 1. DT structure.

The literature showed increased interest in virtual sensors for wind turbine applications. Li and Shen [4] introduced a DT-driven sensing methodology that utilized virtual sensor arrays and a spatiotemporal network to detect faulty wind speed sensors, verified their accuracy, reconstructed normal behaviors, and enhanced the reliability of sensors in wind turbines. Abdullahi et al. [8] proposed the utilization of fog computing architecture to enhance the efficiency of wind turbines based on sensory data from real turbines. Dimitrov and Göçmen [9] introduced machine learning-based virtual sensors, showcasing their effectiveness in predicting blade root bending moment, detecting wind turbine wake center location, and forecasting blade tip-tower clearance by establishing mathematical relationships between the quantities of interest and other measurable sensor readings. Kamel et al. [10] proposed a data-driven virtual sensor based on a hybrid machine learning approach, combining a linear state-space model with a non-linear neural network, to accurately estimate internal loads on wind turbine bearings. Their method achieved a high correlation coefficient of 98% in the time domain and frequency signature, enabling applications like real-time force estimation and model predictive control. Nabiyan [11] et al. implemented a mechanics-based DT for a 2 MW offshore WTG monitoring approach using sparse measurement data. The proposed model updating approach accurately estimated unmeasured responses and input forces, demonstrating better results compared to a modal-based model updating method, with the added benefit of input load identification and uncertainty quantification. Kusiak et al. [12] introduced a data-driven virtual wind speed sensor for wind turbines using historical wind farm data and various data-mining algorithms. The resulting virtual sensor, developed based on wavelet-transformed data, offered potential applications in online monitoring, sensor calibration, and turbine control for utility-scale wind turbines.

This paper highlights the usage of DT as a virtual sensor for WTG. The primary objective is to present a pioneering approach that leverages DT to enhance sensor capabilities and address the inherent limitations of conventional physical sensors. It is organized as follows. Section 1 introduces DTs and their prospective applications for WTG. Section 2 proposes the mathematical models of the WTG from both mechanical and electrical perspectives. In Section 3, the main three pillars of DT are described in detail. Section 4 provides the primary test results of the DT model. Section 5 highlights the main paper's findings. Finally, conclusions and future directions are addressed in Section 6.

2. Wind Turbine Generator Basic Principles

The WTG comprises two distinct models: the mechanical turbine model and the electric PMSG model.

2.1. Wind Turbine Mathematical Model

The objective of this section is to model the aerodynamic aspects of WTG. The modeling approach will be straightforward, focusing on the wind profile and wind turbine models. The conversion of wind kinetic energy into mechanical energy is facilitated by the turbine. Additionally, the amount of kinetic energy contained in the air is directly proportional to the area perpendicularly aligned with the wind speed direction [13].

Wind power (*Pwind*) can be expressed as:

$$Pwind = \left(\frac{1}{2}\right) * \rho * A * V^3 * X_c \tag{1}$$

where:

ρ = density of air.
A = area perpendicular to the wind direction.
V = wind speed.
X_c = coefficient of performance of the turbine.

Taking into consideration the aerodynamics of the blades, the power extracted by a wind turbine represents only a portion of the total power available in the wind. This extracted power can be expressed as:

$$Pextracted = \left(\frac{1}{2}\right) * \rho * A * V^3 * X_c * \eta \tag{2}$$

η = efficiency factor of the wind turbine (accounts for losses due to blade drag, gearbox friction, generator losses, etc.).

$$T = (Pextracted * 60)/(2 * \pi * \omega) \tag{3}$$

where:

ω = angular velocity of the turbine blades.

2.2. PMSG Mathematical Model

The mathematical model of a permanent magnet synchronous generator (PMSG) can be derived from its equivalent circuit as shown in Figure 2 [14].

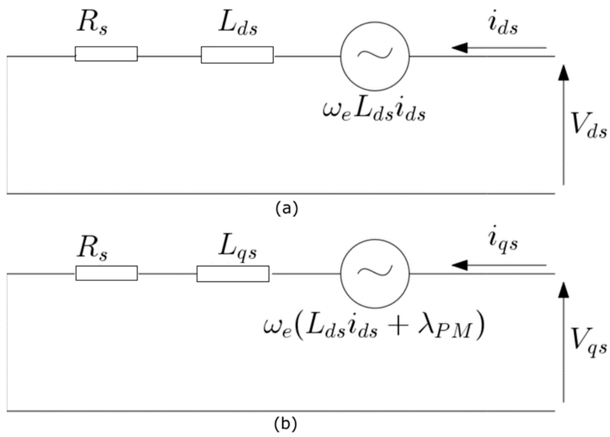

Figure 2. (**a**,**b**) PMSG equivalent circuit.

The d–q model is a two-axis model that simplifies the analysis of the PMSG. The d-axis is aligned with the rotor magnetic field, while the q-axis is perpendicular to it. The d–q model allows us to analyze the electrical and magnetic components of the generator separately.

The equations of the d–q model of a PMSG can be derived as follows:

The voltage equations for the d- and q-axis are:

$$vd = R * ids + \omega e * \psi q \ vq = R * iqs - \omega e * \psi d + \omega m * Ld * ids \tag{4}$$

where R is the stator resistance, ωe is the electrical angular velocity, ωm is the mechanical angular velocity, and Lm is the magnetizing inductance.

The flux linkages in the d- and q-axis are given by:

$$\psi d = Ld * ids + Lmd * iqs \tag{5}$$

$$\psi q = Lq * iqs + Lmq * ids \tag{6}$$

where Ld and Lq are the self-inductances of the stator, and Lmd and Lmq are the mutual inductances between the d- and q-axis.

The electromagnetic torque produced by the generator is given by:

$$Te = (3/2) * P * (\psi d * iqs - \psi q * ids) \tag{7}$$

where Te is the electromagnetic torque, P is the number of poles.

The mechanical equation of the generator is given by:

$$J * d\omega m/dt = Te - Tl - B * \omega m \tag{8}$$

where J is the moment of inertia of the rotor, Tl is the load torque, and B is the viscous friction coefficient.

These equations describe the dynamic behavior of the PMSG in the d–q reference frame.

2.3. Combined WTG Mathematical Model

In this section, a combination formula between both wind turbine and PMSG mathematical models is developed.

The electromagnetic torque produced by the generator is proportional to the product of the magnetic flux and the current in the generator. The magnetic flux, in turn, is proportional to the magnetic field strength and the area of the magnetic circuit. In the case of a WTG, the wind speed affects the magnetic field strength by changing the rotational speed of the generator and the velocity of the air flowing through it.

The relation between the electromagnetic torque produced by the generator and the wind speed can be derived as follows:

The mechanical power from Equation (1) converted into electrical power by the generator can be expressed as:

$$Pg = Pgmax \, * \, (\lambda - \lambda min)/(\lambda rated - \lambda min) \tag{9}$$

where $Pgmax$ is the maximum power output of the generator, λ is the tip speed ratio (TSR), λmin is the minimum TSR required to start the rotor, and $\lambda rated$ is the rated TSR.

The electromagnetic torque produced by the generator can be expressed as:

$$Te = Pg/\omega e \tag{10}$$

where ωe is the electrical angular velocity of the generator.

The electrical angular velocity of the generator is related to the mechanical angular velocity by:

$$\omega e = \omega m/P \tag{11}$$

where P is the number of poles of the generator.

The mechanical angular velocity of the generator is related to the wind speed by:

$$\omega m = \lambda \, * \, V/R \tag{12}$$

where R is the radius of the rotor.

Substituting Equations (10)–(12) into Equation (9) and simplifying, we obtain:

$$Te = (Pgmax \, * \, \lambda/P) \, * \, ((\lambda - \lambda min)/(\lambda rated - \lambda min)) \, * \, (R/V2) \tag{13}$$

This equation shows the relation between the electromagnetic torque produced by the generator and the wind speed. It indicates that the torque is proportional to the tip speed ratio, which is a function of the wind speed and the rotor radius. The torque is also proportional to the maximum power output of the generator and the number of poles, and inversely proportional to the square of the wind speed.

The power generated by a wind turbine generator is dependent on the wind speed and other factors such as the swept area of the rotor, the efficiency of the generator, and the electrical load on the generator. The relation between the wind speed and generated power can be derived as follows:

The electrical power generated by the generator is given by:

$$Pe = Pg \, * \, \eta g \tag{14}$$

where ηg is the efficiency of the generator.

From (9) and (14) the electrical power generated is related to the wind speed as follows:

$$Pe = (1/2) \, * \, \rho \, * \, A \, * \, V3 \, * \, X_c \, * \, \eta g \, * \, (\lambda - \lambda min)/(\lambda rated - \lambda min) \tag{15}$$

The equations show the relationship between the wind speed and generated power by the wind turbine generator. It indicates that the generated power is proportional to the cube of the wind speed and the swept area of the rotor. It is also proportional to the power coefficient, which is a function of the aerodynamic properties of the rotor blades. The generated power is further multiplied by the generator's efficiency to obtain the electrical power output of the wind turbine generator.

3. WTG—Digital Twin Development Procedures

DT consists of three primary elements: physical model, virtual model, and interconnecting interface linking the two. The physical model serves as a representation of the physical entity or system, like a test bench. The virtual model, on the other hand, is a digital portrayal of the physical object. The interconnecting interface establishes a connection between both models, enabling data exchange. This data can be utilized to monitor the physical object or system and forecast its future performance.

3.1. WTG Physical Model (Test Bench)

The physical model of the direct drive WTG test bench is a comprehensive setup designed to simulate and evaluate its performance. This test bench allows for thorough testing and analysis of the generator under various scenarios of loading and wind conditions.

At the core of the test bench is a 600 W, eight poles surface-mounted PMSG, which serves as the primary power-generating component. The PMSG is connected to a servo motor, which acts as a load emulator, replicating different mechanical and electrical loads that the generator may encounter in real-world wind turbine applications. This configuration enables the evaluation of the generator's response and efficiency under varying conditions. Table 1 provides an insight into the PMSG parameters. The mechanical parameters of the WTG are illustrated in Table 2.

Table 1. PMSG parameters.

Parameter	Description	Value	Unit
p	Number of pole pairs	8	-
Nr	Rated speed	750	rpm
Pr	Rated output power	600	W
Ir	Rated current	2.73	A
KT	Torque constant	0.12	Nm/A
J	Rotor inertia	0.002	kg $\cdot$m^2
η	Efficiency	92%	-

Table 2. Mechanical parameters of WTG.

Parameter	Description	Value	Unit
N_s	Startup wind speed	3	m/s
N_c	Cut-in wind speed	3.5	m/s
N_r	Rated wind speed	12	m/s
P_r	Max wind speed	25	m/s
L_p	Blade length	1.5	m

To accurately measure and monitor the performance of the generator, a power analyzer and data acquisition system (DAS) are integrated into the test bench. The power analyzer enables the measurement and analysis of electrical variables such as voltage, current, power output, and power quality indicators. The DAS captures and records these measurements for further analysis and evaluation.

To facilitate precise control over the servo motor and its loading characteristics, a servo drive system is employed. This servo drive system enables the test bench to simulate different loading profiles and adjust the load dynamically, providing flexibility in replicating various wind conditions and evaluating the generator's behavior under different operational scenarios. Figure 3 shows the WTG test bench.

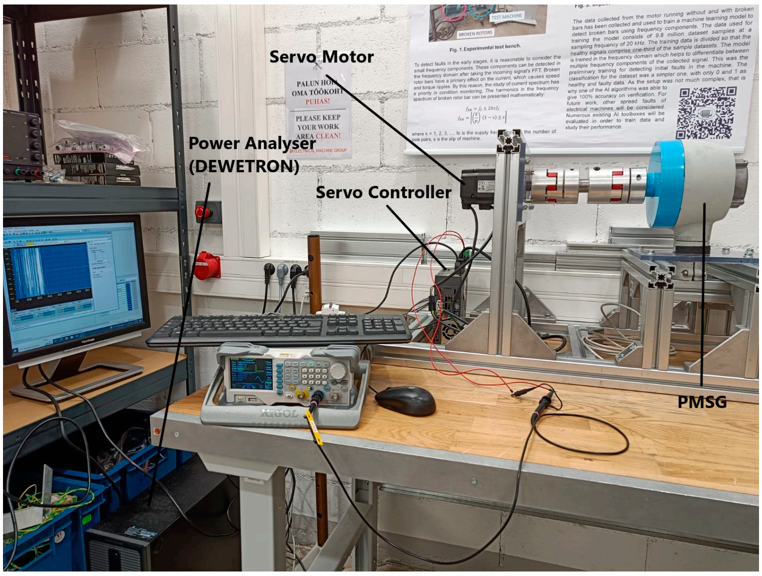

Figure 3. WTG test bench.

3.2. WTG Virtual Model

The WTG virtual model created using MATLAB Simulink is a representation of a system that combines the behavior of a wind turbine and a PMSG based on the mathematical equations of combined WTG. This model aims to simulate the performance and characteristics of a wind turbine generator under various operating conditions. Figure 4 shows the WTG virtual model.

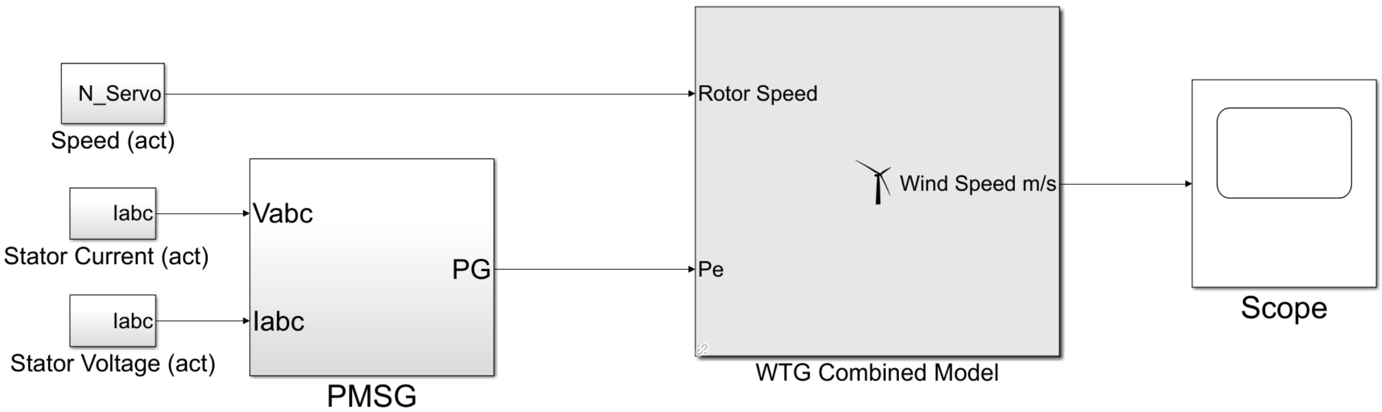

Figure 4. WTG virtual model.

The model typically consists of several interconnected blocks in Simulink, each representing a specific component or subsystem of the wind turbine generator system. These blocks are connected through signal lines, indicating the flow of information or energy between them. At a high level, the model includes the following components:

(a) PMSG model:

This block receives the values of stator currents, voltages, and the rotor speed as inputs. Using these inputs, it calculates the produced power output of the PMSG. The rotor speed provides information about the rotational speed of the generator. By analyzing these inputs, the PMSG block calculates the power generated by the generator.

(b) Wind Turbine Combined Model:

The wind turbine combined model block uses the torque and power information from the PMSG, along with the rotor speed, to infer the wind speed that would be required to generate such mechanical power. This estimation assumes that the wind turbine system operates within certain efficiency and power capture characteristics, which are incorporated into the mathematical model.

3.3. Data Exchange Set (Service Unit)

The service unit, also known as the data exchange set, plays a crucial role in facilitating real-time data exchange between physical and virtual models. In this, an ActiveX server was utilized to retrieve measured data from the DAS channels and transfer it to the MATLAB workspace.

By employing an ActiveX server, we establish a connection between the DAS channels and MATLAB, allowing for retrieving real-time data. The ActiveX server is set up to interface with the DAS channels, which are responsible for acquiring data from physical sensors or devices. The measured data from the DAS channels is fetched by the ActiveX server. The ActiveX server communicates with MATLAB, using the appropriate interface or API, to transfer the acquired data to the MATLAB workspace. Once the data are available in the MATLAB workspace, it can be directly fed into the Simulink model for processing and analysis. This approach allows for seamless integration between physical measurements and virtual modeling in Simulink, enabling the incorporation of real-time data into simulations.

4. WTG-DT Model Validation

Validation and tuning of the simulation model with the physical model are crucial steps in the DT development process. This step ensures that the DT accurately represents the behavior and performance of the real-world WTG.

To validate and tune the simulation model, real data obtained from the test bench are utilized and serve as the input to the simulation model, allowing it to replicate the operating conditions and parameters of the physical model. By using the actual data from the test bench, the simulation model can be evaluated for its ability to accurately mirror the performance of the physical WTG.

The servo motor drove the WTG under different speed conditions to emulate different wind speeds. The WTG output was kept open with no loading as a primary stage. Using DAS, the data collected from the tests were the PMSG three-phase voltage, current, generated power, and rotor speed.

To validate the accuracy of the model, a series of comprehensive tests were conducted on the wind turbine. The initial phase involved testing the turbine under no loading conditions, with the rotation driven solely by a servo motor operating at various speeds. The resulting data from these tests were meticulously recorded and subsequently utilized to feed the simulation model of the wind turbine.

Moving forward, the validation process proceeded to the second step, which entailed subjecting the actual wind turbine to a range of diverse wind speed conditions. During these rigorous tests, the real-time wind speed was precisely measured using a dedicated wind speed sensor (anemometer). By comparing the data obtained from both the simulated model and the real-world tests, an extensive analysis was conducted to identify any similarities or discrepancies. Figure 5 shows some results of sampled actual vs. estimated wind speed.

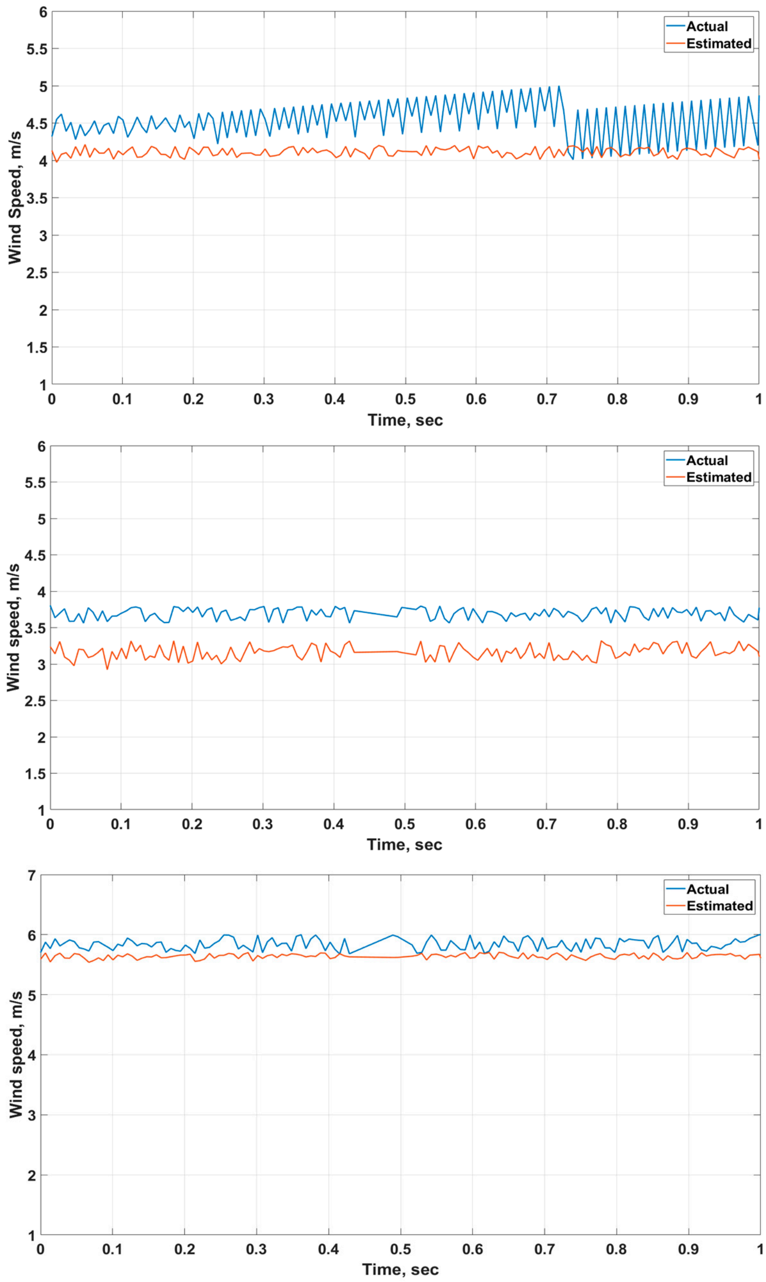

Figure 5. Actual vs. estimated wind speed values from DT model.

It was observed that the estimated wind speeds derived from the simulation model closely approximated around 83% of the corresponding values obtained from the wind speed sensor during the real-world tests. However, it is essential to note that certain external factors affecting the performance of the actual wind turbine were not adequately accounted for in the simulation. These factors, which cannot be entirely captured in the model, may explain the slight variance between the estimated and real wind speeds.

The comprehensive validation process undertaken, involving both controlled servo motor tests and real-world weather condition experiments, provides substantial evidence supporting the reliability of the model. Nevertheless, it is crucial to consider the limitations of any simulation model and acknowledge the impact of external factors on the actual performance of the wind turbine. The following Table 3 shows duplicated results.

Table 3. Comparison between obtained results from real and virtual sensors.

Generated Power (W)	Actual Wind Speed (m/s)	Estimated Wind Speed (m/s)	Rotor Speed (rpm)	MAE
112	3.77	3.2	113	0.57
194	3.98	3.59	195	0.50
253	4.46	4.1	256	0.30
336	5.16	4.8	339	0.36
469	5.91	5.6	471	0.31
507	6.21	5.9	509	0.31
543	6.35	6.1	546	0.25
579	6.76	6.5	583	0.26

The mean absolute error (MAE) values in the provided table reflect the average magnitude of the discrepancies between the estimated wind speeds and the actual wind speeds. The relatively small MAE values across the data points (ranging from approximately 0.26 to 0.57) suggest that the wind speed estimation model is performing with good accuracy. These low MAE values indicate that, on average, the estimated wind speeds are very close to the actual wind speeds for the given data points.

5. Discussion

The application of DT technology as a virtual sensor for WTG has shown promising results in this study. The DT model, based on the provided wind turbine specifications and an estimation method, was used to estimate wind speeds based on generated power. The obtained results were then compared with real-world data collected from wind speed sensors under different generated power conditions. The conducted study was associated with one condition of no loading.

The comparison between the estimated wind speeds and the real wind speeds demonstrates the effectiveness of DT as a virtual sensor for wind turbine generators. The estimated wind speeds exhibited a close agreement with the real wind speeds within 80% for the given generated power values.

However, it is important to acknowledge the limitations and the inherent uncertainties associated with the estimation method used. The accuracy of the estimated wind speeds depends on various factors, including the wind turbine's design, efficiency, and environmental conditions, which may not be fully captured in the DT model. Additionally, the estimation method itself introduces certain assumptions and simplifications that can contribute to discrepancies between the estimated and real wind speeds.

6. Conclusions

This research underscores the significance of digital twins as a valuable tool for wind turbine applications. The proposed DT-based sensing methodology offers a promising solution to the limitations of physical wind speed sensors, contributing to the overall efficiency and performance of wind turbine generators.

The test bench of a direct drive WTG based on a permanent magnet synchronous generator (PMSG) served as a physical platform for developing and validating the DT model. MATLAB/Simulink was utilized to derive the mathematical model and develop the virtual WTG model. The integration of a data acquisition system (DAS) equipped with an ActiveX server facilitated seamless real-time data exchange between the physical and virtual models.

The validation and tuning process involved utilizing real sensory data from the physical turbine model to ensure the accuracy and reliability of the DT-based virtual sensor. The results obtained from the developed DT model have demonstrated its capability to estimate wind speed based on the generated power, showcasing its potential as a reliable alternative to traditional physical wind speed sensors.

In conclusion, while this study has made significant contributions to the understanding of DT-based virtual sensors for wind turbine applications, there are several limitations that should be addressed in future research. These include conducting tests under varied loading conditions, incorporating additional factors that can affect WTG performance, leveraging artificial intelligence and machine learning techniques for advanced analysis, and expanding the scope of the study to include diverse WTG designs. By addressing these limitations, future studies can further enhance the accuracy, reliability, and applicability of DT-based virtual sensors in the wind energy industry.

Author Contributions: Conceptualization, M.I. and A.R.; methodology M.I.; software, T.V.; validation, A.K. and T.V.; formal analysis, M.I.; investigation, A.K.; resources, T.V.; writing—original draft preparation, M.I.; writing—review and editing, A.R., J.Z. and V.K.H.; supervision, R.P.; project administration, R.P. All authors have read and agreed to the published version of the manuscript.

Funding: The "Industrial Internet methods for electrical energy conversion systems monitoring and diagnostics" benefits from an 993.000 EUR grant from Iceland, Liechtenstein, and Norway, through the EEA Grants. The aim of the project is to provide research in the field of energy conversion systems and to develop artificial intelligence and virtual emulator-based prognostic and diagnostic methodologies for these systems. The project contract with the Research Council of Lithuania (LMTLT) No is S-BMT-21-5 (LT08-2-LMT-K-01-040).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Ibrahim, M.; Rassõlkin, A.; Vaimann, T.; Kallaste, A. Overview on Digital Twin for Autonomous Electrical Vehicles Propulsion Drive System. *Sustainability* **2022**, *14*, 601. [CrossRef]
2. Rassõlkin, A.; Orosz, T.; Demidova, G.L.; Kuts, V.; Rjabtšikov, V.; Vaimann, T.; Kallaste, A. Implementation of digital twins for electrical energy conversion systems in selected case studies. *Proc. Est. Acad. Sci.* **2021**, *70*, 19–39. [CrossRef]
3. Sivalingam, K.; Sepulveda, M.; Spring, M.; Davies, P. A Review and Methodology Development for Remaining Useful Life Prediction of Offshore Fixed and Floating Wind turbine Power Converter with Digital Twin Technology Perspective. In Proceedings of the 2018 2nd International Conference on Green Energy and Applications (ICGEA), Singapore, 24–26 March 2018; pp. 197–204. [CrossRef]
4. Li, Y.; Shen, X. A Novel Wind Speed-Sensing Methodology for Wind Turbines Based on Digital Twin Technology. *IEEE Trans. Instrum. Meas.* **2022**, *71*, 2503213. [CrossRef]
5. Mardiyah, N.; Setyawan, N.; Retno, B.; Has, Z. Active fault tolerance control for sensor fault problem in wind turbine using SMO with LMI approach. In Proceedings of the 2018 5th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI), Malang, Indonesia, 16–18 October 2018; pp. 336–340. [CrossRef]
6. Trevathan, J.; Read, W.; Sattar, A.; Schmidtke, S.; Sharp, T. The Virtual Sensor Concept: Separating Sensor Software from the Hardware. In Proceedings of the 2020 IEEE SENSORS, Rotterdam, Netherlands, 25–28 October 2020. [CrossRef]
7. Toso, F.; Torchio, R.; Favato, A.; Carlet, P.G.; Bolognani, S.; Alotto, P. Digital twins as electric motor soft-sensors in the automotive industry. In Proceedings of the 2021 IEEE International Workshop on Metrology for Automotive (MetroAutomotive), Bologna, Italy, 1–2 July 2021; pp. 13–18. [CrossRef]
8. Abdullahi, I.; Perinpanayagam, S.; Hamidu, I. A Fog Computing Based Approach Towards Improving Asset Management and Performance of Wind Turbine Plants Using Digital Twins. In Proceedings of the 2022 27th International Conference on Automation and Computing (ICAC), Bristol, UK, 1–3 September 2022. [CrossRef]
9. Dimitrov, N.; Göçmen, T. Virtual sensors for wind turbines with machine learning-based time series models. *Wind Energy* **2022**, *25*, 1626–1645. [CrossRef]
10. Kamel, O.; Kretschmer, M.; Pfeifer, S.; Luhmann, B.; Hauptmann, S.; Bottasso, C.L. Data-driven virtual sensor for online loads estimation of drivetrain of wind turbines. *Forsch. Im Ing./Eng. Res.* **2023**, *87*, 31–38. [CrossRef]
11. Nabiyan, M.S.; Khoshnoudian, F.; Moaveni, B.; Ebrahimian, H. Mechanics-based model updating for identification and virtual sensing of an offshore wind turbine using sparse measurements. *Struct. Control. Health Monit.* **2021**, *28*, e2647. [CrossRef]

12. Kusiak, A.; Zheng, H.; Zhang, Z. Virtual Wind Speed Sensor for Wind Turbines. *J. Energy Eng.* **2021**, *137*, 59–69. [CrossRef]
13. Kulkarni, H.; Kulkarni, A.; Pagire, T.; Magdum, S. Mathematical Modeling, Installation of Wind turbine and its analysis in MATLAB. In Proceedings of the 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 16–18 March 2022; pp. 142–149. [CrossRef]
14. Aziz, D.; Jamal, B.; Othmane, Z.; Khalid, M.; Bossoufi, B. Implementation and validation of backstepping control for PMSG wind turbine using dSPACE controller board. *Energy Rep.* **2019**, *5*, 807–821. [CrossRef]