mathematics

Article

Digital Twin-Based Approach for a Multi-Objective Optimal Design of Wind Turbine Gearboxes

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Abstract: Wind turbines (WT) are a clean renewable energy source that have gained popularity in recent years. Gearboxes are complex, expensive, and critical components of WT, which are subject to high maintenance costs and several stresses, including high loads and harsh environments, that can lead to failure with significant downtime and financial losses. This paper focuses on the development of a digital twin-based approach for the modelling and simulation of WT gearboxes with the aim to improve their design, diagnosis, operation, and maintenance by providing insights into their behavior under different operating conditions. Powerful commercial computer-aided design tools (CAD) and computer-aided engineering (CAE) software are embedded into a computationally efficient multi-objective optimization framework (modeFrontier) with the purpose of maximizing the power density, compactness, performance, and reliability of the WT gearbox. High-fidelity models are used to minimize the WT weight, volume, and maximum stresses and strains achieved without compromising its efficiency. The 3D CAD model of the WT gearbox is carried out using SolidWorks (version 2023 SP5.0), the Finite Element Analysis (FEA) is used to obtain the stresses and strains, fields are modelled using Ansys Workbench (version 2024R1), while the multibody kinematic and dynamic system is analyzed using Adams Machinery (version 2023.3, Hexagon). The method has been successfully applied to different case studies to find the optimal design and analyze the performance of the WT gearboxes. The simulation results can be used to determine safety factors, predict fatigue life, identify potential failure modes, and extend service life and reliability, thereby ensuring proper operation over its lifetime and reducing maintenance costs.

Keywords: digital twin; multi-objective optimization; multibody simulation; finite element analysis; structural optimization; wind turbine; gearbox

MSC: 70E55; 78M10; 78M50

Citation: Llopis-Albert, C.; Rubio, F.; Devece, C.; García-Hurtado, D. Digital Twin-Based Approach for a Multi-Objective Optimal Design of Wind Turbine Gearboxes. *Mathematics* **2024**, *12*, 1383. https://doi.org/10.3390/math12091383

Academic Editors: Yong He and Nicu Bizon

Received: 26 March 2024
Revised: 25 April 2024
Accepted: 30 April 2024
Published: 1 May 2024

1. Introduction

Wind power is a clean and renewable energy source which is gradually gaining share in the total global supply of energy, while helping to achieve the Sustainable Development Goals (SDGs) [1,2]. In fact, the global installed wind power capacity will exceed 1 TW by the end of 2023 [3]. The operation and maintenance (O&M) of wind energy expenses make up a large and possibly rising portion of the cost of energy (COE), particularly when it decreases, because of lower initial costs and higher performance. O&M may be responsible for 15~20% of the COE of wind energy, while for offshore WTs, the ratio is 25~35% [3].

The gearbox is a complex and expensive component of a Wind Turbine (WT), which is responsible for converting the relatively slow rotations of a turbine blades into the high speeds needed to generate electricity. The dynamics of a WT gearbox can be affected by several factors including the wind speed changes, the rotor speed, the gear ratio, the stiffness of the components, the lubrication of the gears, and the applied forces (including the meshing forces, the centrifugal forces, and the gyroscopic forces) which can lead to fatigue damage.

The main sources of the failures in WT gearboxes and bearings encompass the fatigue, wear, misalignment, corrosion, vibrations, and resonances in the drivetrain components, and harsh environments such as wind gusts, rain, snow, high temperatures, moisture, and dust. This leads to a significant cost of maintenance due to the high cost of spare parts, the need for specialized technicians, the WT downtime costs, and the insurance costs to cover possible failures. Furthermore, as wind turbines increase in size and capacity, gearbox failures are expected to continue being a problem for wind power plant operators unless they can be reproduced in the laboratory, computationally modelled, and compared with actual power plant results. In fact, WT gearboxes account for over 20% of WT downtimes, and they require a replacement after only 6 to 8 years, far less time than the anticipated 25 years of WT lifespan [4].

In this sense, the size and power of wind turbine gearboxes continue to grow, reaching up to 15 megawatts (MWs) and 3 m in diameter, respectively. Torque densities of 200 newton meters per kilogram and speed-increasing ratios up to 200 are now possible with multistage gearboxes using four or more planet epicyclic systems [5]. Modular gearboxes have been designed to further reduce costs through the economies of scale. According to the IEC 61400-4 and the American Gear Manufacturers Association (AGMA) 6006 gearbox design specifications, gearboxes must have a minimum of 20-year lifespan. O&M and monitoring activities are required for components that present a fatigue life less than the gearbox.

There are two main types of gearboxes used in WTs, planetary gearboxes, and parallel-shaft gearboxes. Planetary gearboxes are more compact than parallel-shaft gearboxes, but they are also more expensive. The gearbox comprises many elements, including the rotating shafts, gears, and bearings, that entail different failure modes and reliabilities. Different standards and technical specifications deal with materials, processing, manufacture, and gearbox reliability. The reliability calculation and safety factors consider gear tooth scuffing, flank fracture and surface durability (pitting), bending strength, rolling contact fatigue, and shaft fatigue fracture. Qualitative evaluations can be made of other bearing failures, such as surface-initiated fatigue (for instance, micropitting), corrosion, adhesive wear, electrical damage, and white-etching fractures [6,7]. Eventually, WT gearbox failure detection and remaining useful life (RUL) prediction have been tackled using a wide range of techniques, comprising machine and deep learning, finite element modeling, Bayesian inference, supervisory control and data acquisition (SCADA) systems, and physics-informed models, etc. [8–12].

In this sense, three broad categories are presented for gearbox dynamic modelling in terms of the Degrees of Freedom (DOF) which cover a stiff multibody model that is only torsional; a rigid multibody model that has three, four, or six DOF; or a flexible multibody model [13]. The effects of gear and shaft lateral movements are not considered by the purely torsional stiff multibody model since it only considers the torsional DOF. Planar motion or motion in three-dimensional space are considered by stiff multibody models with three, four, or six DOF. Due to its excellent computing efficiency and tolerable analytical accuracy, it is the most widely used analysis model. The flexibility of the gear shaft, gearbox housing, planet carrier, or ring gear is frequently considered by the flexible multibody model, so that it is the most realistic model to capture the dynamic features of the wind turbine drivetrain, despite its lower computation efficiency.

Classical approaches, such as analytic techniques and lumped-parameter methods, are used for modeling gears and bearings due to their computational efficiency [14]. For more in-depth studies of failure modes, powerful commercial multibody simulation software packages and finite element analysis have been coupled, e.g., [15–20]. The increased accuracy of these techniques comes at the expense of an increased computational burden which in practice is only applicable to static simulations. To reduce the computational cost of the finite element method (FEM) in dynamic simulations, two strategies have recently been applied. The first strategy combines the FEM with semi-analytic results from classic contact theory to remove the need for highly refined finite element meshes in the contact zone [21]. The second strategy decreases the number of degrees of freedom in the finite element models through model order reduction approaches that are designed expressly for dynamic contact problems [22]. Additionally, the optimization of the WT drivetrain has also been investigated [23,24].

The use of plain bearings in the gearbox are gaining ground because of their advantages in terms of torque density and lifespan, which is only limited by wear [19]. Additionally, the design and O&M of gearboxes strongly depends on surface engineering and lubrication [25–28].

To face these problems, digital twins (DTs) and signal-based and data-driven surrogate models have recently emerged in the wind energy industry, as they can be used for health monitoring and for the predictive maintenance of the WT, fault detection and diagnostics, the optimization of the WT performance, identifying opportunities for efficiency improvements and optimal operation, enhancing overall wind farm management, better decision-making and resource allocation, and minimizing downtime and repair costs [29].

DTs represent one more step in the disruptive effect of the global digital transformation process [30]. A DT is a virtual representation of a physical system that can used to simulate the dynamic behavior and fatigue life prediction of the physical system under a variety of operating conditions and to predict and improve its performance and reliability [31]. DTs make use of real-time data obtained from sensors instrumented in physical wind turbines (such as SCADA systems) to improve results or validate them by comparing those data with the DT expected behavior obtained from simulating different operating conditions [32]. Deviations from the expected performance can indicate potential faults or failures, allowing operators to take corrective actions promptly.

On the one hand, the virtual representation of the WT can be carried out by means of high-fidelity models, such as comprehensive finite element and multi-body simulation models. They can produce very precise estimations but it is computationally very expensive to calibrate using data collected from the real wind turbine. On the other hand, low-fidelity techniques that make use of Reduced Order Models (ROM) are computationally inexpensive to adjust but lack performance [32]. Consequently, to provide real-time simulations for predictive maintenance and monitoring purposes, wind turbine drivetrain modelling relies on efficient ROM, which presents a lower computational cost if compared with traditional approaches. ROM are built by assuming the simplifications of the underlying physics phenomena and using data-driven surrogate models. Hence, DTs combine physics-informed models (e.g., machine learning techniques, such as Physics-Informed Neural Networks, PINNs) and operational data obtained from SCADA systems to provide data-driven surrogate models [33]. The SCADA system records critical WT parameters from a high-fidelity sensor network such as drivetrain vibrations, temperatures, oil quality, surface roughness, high-quality pictures of damaged gear teeth, etc. For that, machine learning or deep learning techniques, statistical models, and stochastic modelling approaches are frequently used to implement the physics-informed models, to process the gathered real data, to reduce the discrepancy between observed data and model projections, and to assess the uncertainty in predicting the remaining useful life (or time to failure) of a WT gearbox [33].

Ref. [29] carried out a literature review of wind turbine DTs dealing with potential modelling techniques focused on model fidelity and computational load, ranging from simplified lumped parameter models to advanced numerical Finite Element Method (FEM)-based models. The work referred to in [31] introduced DT modeling for monitoring the RUL of gearboxes in floating offshore WT drivetrains by means of a multi-degree of freedom torsional model. The work referred to in [32] presented a hybrid DT application, adapted for monitoring WT main bearing fatigue, by combining physics-informed models and data-driven kernels to quantify uncertainty in grease degradation. The work referred to in [33] developed a DT of WT gear stages using real-time virtual sensing in which the state equations are derived analytically by means of the bond graph method. The work referred to in [34] presented a DT for the condition monitoring of drivetrains on floating offshore WT, based on a torsional dynamic model, online measurements, and fatigue damage estimation with the aim of estimating the RUL. The work referred to in [35] applied machine learning techniques to a cloud-based digital twin for virtually monitoring wind turbines and performing a predictive model to forecast wind speed and predict the generated power. The work referred to in [36] dealt with the fault diagnosis of WT planetary gear, based on a digital twin implemented in the Unity3D platform, which uses an empirical mode decomposition and an atom search optimization–support vector machine model. The work referred to in [37] used an artificial neural network for data-driven fault diagnosis of DT applied to WT gearboxes. The work referred to in [38] developed a DT virtual sensor for online load monitoring and subsequent RUL assessment of WT gearbox bearings, which makes use of a SCADA system with a physics-based gearbox model. The work referred to in [39] implemented, verified, and validated a physics-based DT and applied it to a floating offshore WT to estimate the aerodynamic loads, wind speed, and section loads along the tower for estimating the fatigue lifetime of the tower.

The use of a DT provides several advantages over traditional ones, such as the flexibility in adapting to complex non-linear systems. However, to that end, physics-informed models must be compatible with the linear algebra commonly used in machine learning models [32]. Furthermore, the accuracy and quality of the physics-based models are also critical to the efficacy of these approaches, since their main drawback is the level of fidelity. Likewise, the computational cost of data processing is still an issue in large-scale applications. As a result, DTs help to reduce the cost of wind energy and to improve the reliability of wind turbines, which has promoted their dissemination in the academic world and their applications in the engineering field [40–42].

This paper goes a step further than the current literature by presenting and applying a digital twin approach to different case studies based on a computationally efficient multi-objective optimization framework, which couples powerful commercial computer-aided design tools (CAD) and computer-aided engineering (CAE) software for fault diagnosis, health monitoring and diagnosis, analyzing variable operation conditions, uncertainty assessment and sensitivity analysis in operating parameters, optimal predictive maintenance, and the efficiency improvement of wind turbine gearboxes.

The rest of this paper is organized as follows. Section 2 describes a digital twin-based approach of the WT gearbox. Section 3 presents the different case studies, while Section 4 discusses the results of the simulations. Section 5 concludes the paper and discusses the future work.

2. Digital Twin-Based Approach of the WT Gearbox

The design of a WT gearbox requires the use of complex optimization–simulation techniques that allow for estimating the key parameters and the impact on their dynamic behavior and fatigue reliability. The methodology presents an efficient design and representation of a real-world WT gearboxes by posing a multi-objective optimization framework to come up with a good compromise between the design variables and including a wide range of advantages beyond traditional engineering methods. The developed DT leads to the following:

- Efficient design optimization:
    - The methodology presents an efficient design and representation of real-world wind turbine gearboxes through a multi-objective optimization framework. It leads to a more compact gearboxes while maintaining power density.
    - It aims to find a good compromise between design variables to enhance power density while maintaining compactness. It allows us to assess the trade-offs between the competing design variables, since certain combinations of these

variables favor the objective of increasing power density without compromising efficiency, while other combinations worsen it.
  - It is easily extendable to the design of other parts of the WT drivetrain.
- The use of robust high-fidelity and well-known engineering tools embedded in a multi-objective optimization framework:
  - It allows us to deal with a wide range of objectives and obtain accurate results.
- Optimal design for performance:
  - The results provide information on the optimal design of wind turbine gearboxes with minimum volume, weight, and maximum stresses and strains achieved without compromising efficiency. This leads to increased compactness and power density compared to other gearbox designs, enhancing overall performance.
  - It allows us to perform a fatigue analysis to assess if the optimized designs sustain accumulated damage, leading to a minimum defined RUL and safety factors.
  - This methodology allows us to deal with different WT gearbox configurations (planetary gear and parallel shaft gear arrangements, multistage transmissions, gear ratios, straight and spiral teeth, etc.).
- Automated optimization:
  - The developed digital twin enables automated optimization by integrating powerful engineering tools into a single workflow.
  - This allows for the evaluation of thousands of designs to achieve optimized gearbox configurations.
- Comprehensive analysis:
  - This methodology considers the kinematics and dynamics behavior of multistage transmissions in wind turbine gearboxes.
  - It includes the structural integrity analysis of mechanical components, material properties, and geometric characteristics.
- Real data integration:
  - The digital twin framework can incorporate real data from sensors for testing procedures, maintenance, and the monitoring of wind turbine gearboxes.
  - This integration enhances the predictive capabilities of the digital twin for detecting, diagnosing, and monitoring failures.
  - It manages a broad spectrum of explanatory and response variables.
- Advanced data analysis:
  - This methodology includes cutting-edge data analysis techniques to balance competing design goals.
  - It allows us to derive the Pareto optimal front to provide a deeper understanding of design options and facilitate informed decision-making.
- Support for existing loads:
  - The optimized gearbox designs can support existing loads with maximum power density.
  - The developed framework helps in reducing mechanical failures, vibrations, and increasing the fatigue life of wind turbine gearboxes.
- Efficiency, reliability, and economical issues:
  - Maximizes efficiency and reliability, thus reducing failures and O&M costs.
  - It leads to better decision-making and resource allocation, while minimizing downtime and repair costs.

These contributions highlight the significance of the developed digital twin-based approach in advancing the design and optimization of WT gearboxes for improved efficiency and reliability.

Figure 1 shows the flowchart diagram of the multi-objective optimization framework, based on a digital twin approach. It illustrates the flow of information between the different powerful computer-aided design (CAD) and computer-aided engineering (CAE) commercial software. The digital twin representation enables for an accurate simulation of the behavior of the mechanical components of the gearbox and the associated multi-physics processes. The methodology comprises building a 3D CAD model of the WT gearbox in SolidWorks (developed by Dassault Systèmes), including all the components and their relationships, that allow us to optimize its weight (W), volume (V), and compactness (C). Additionally, a multibody kinematic and dynamic analysis of the WT gearbox is performed through Adams Machinery (developed by Hexagon), which allow us to analyze the fatigue life and provide insights into the design and operation of the systems. Then, an analysis of the structural integrity of the planetary gear stage is carried out using Ansys Workbench (developed by ANSYS, Inc., Canonsburg, PA, USA), which is a general-purpose Finite Element Analysis (FEA) software, with the aim of minimizing the maximum stresses achieved. Eventually, the results are embedded in a multidisciplinary optimization design framework, using the tool modeFrontier (developed by Esteco Sofware Company, Trieste, Italy), with the aim of obtaining the set of design variables that provides the optimal values. In this sense, Adams Machinery is used to determine speed and gear ratios, together with the mechanical loads (forces and momentums) that are applied to the gearbox. Subsequently, using the geometry, material properties, and applied loads, Ansys estimates the maximum von-Mises equivalent stresses (SEQ) and strains achieved that satisfy the optimization problem constraints. This approach circumvents the problem of several multi-body simulation (MBS) models that only support the export of linearized models (state–space representation), that are inadequate in representing the highly non-linear dynamics of drivetrains models [32].

The framework allows us to create a comprehensive and accurate model of a wind turbine gearbox from a single workflow and to automatically evaluate thousands of designs while balancing conflicting objectives to maximize efficiency, improve performance and reliability, and cut operational costs.

The selection of the objectives in the penalty function is based not only on the design requirements regarding the power and gear ratio of the wind turbine, but also to avoid an overparameterized optimization problem. Depending on the problem in hand, the multi-objective optimization framework using modeFrontier enables optimization, using either local (usually gradient based), or global (typically non-gradient based or evolutionary) techniques, or a combination of both. Additionally, a variety of strategies, including multi-strategy optimizers, heuristic optimizers, evolutionary algorithms, and gradient-based algorithms can be used. A thorough discussion of such strategies can be found in the work referred to in [43]. For this study, we have selected the pilOPT approach, because it usually leads to better results than the other algorithms [42]. It is a multi-strategy self-adapting technique that integrates the advantages of global and local search algorithms. The optimal Pareto front is obtained by adjusting the ratio between real and RSM-based (i.e., virtual runs based on Response Surface Methodology) design evaluations on account of their performance. They provide a suitable performance, despite handling complex output functions and restrained problems. It is mainly used for multi-objective problems, but it can also handle single-objective problems. It is advisable to deal with both continuous and discrete variables. Instead, it is not able to manage categorical variables. The fact that just one parameter—the quantity of design evaluations—is required is another benefit. When this number is attained, the algorithm comes to an end in this manner. For the sake of conciseness, the reader is referred to the specialized literature and the user documentation of the engineering tools used in this paper for a thorough explanation of the underlying theory of the multiphysics processes and the modelling implementation details. Note that this methodology requires the design of the 3D mechanical components of the WT gearbox, the calculation of its kinematics and dynamics, and the estimation of stresses and deformations by means of the finite element method (FEM). Therefore, an in-depth explanation of such aspects is unattainable and out of the scope of this paper.

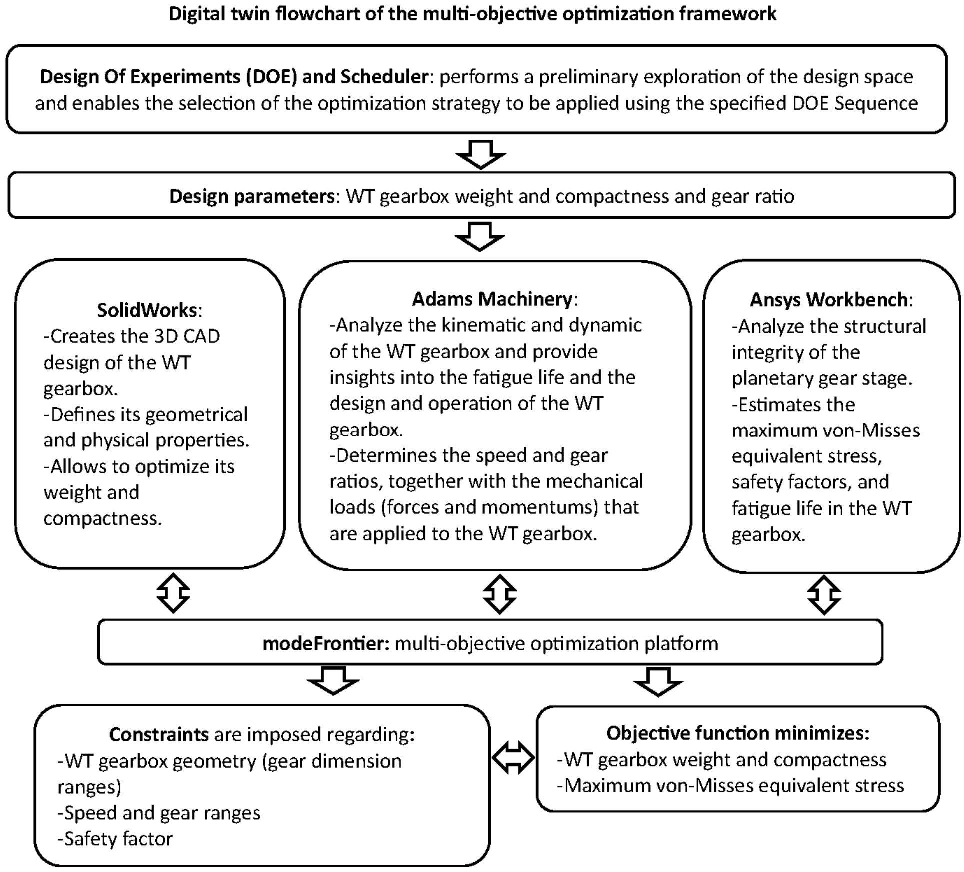

Figure 1. Flowchart of the optimization framework based on a digital twin representation of the system showing the links between the CAD/CAE tools and the flow of information of the multi-physics processes.

It is important to note that, even though the modeFrontier platform has many benefits for the implementation of a multi-objective optimization problem, the reader should be aware that in order to use the platform effectively, advanced modelling skills for both the platform and the embedded engineering tools, as well as knowledge of the underlying physical processes, are necessary.

Then, the presented methodology is in line with the development of clean technologies based on renewable energies for mitigation and adaptation to climate change [1].

3. Application of the Methodology to Different Case Studies

The planetary gear assembly consists of 3 primary components: a ring gear (the outer most gear), 3 planetary gears that are housed by a planetary carrier assembly (the middle gears), and a sun gear (the gear in the center of the gear set) as shown in Figures 2 and 3. Adams Machinery deals with the planetary gear using a geometry-based contact that supports shell-to-shell 3D geometry contact. It calculates true backlash based on the actual working center distance and tooth thickness. It allows for the consideration of out-of-plane motion with the gear pair. The parameters that define the geometry and the material of the planetary gear are presented in Table 1. This study considers a homogeneous material for the gearbox based on structural steel with a density of 7850 kg/m^3, a Young’s modulus of 2.07×10^5 MPa, and a Poisson’s ratio of 0.29.

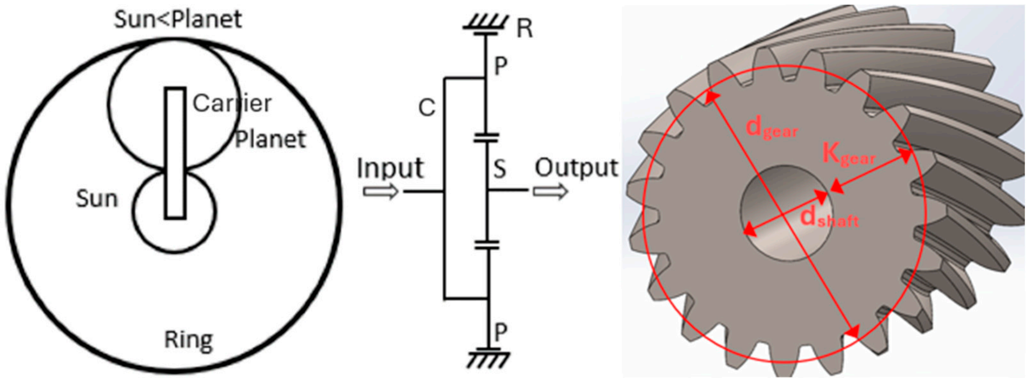

Figure 2. The gear train design used in this study and the representation of the pitch and shaft diameters, together with the parameter K_{gear}. P stands for Planet, C for Carrier, S for Sun, and R for Ring.

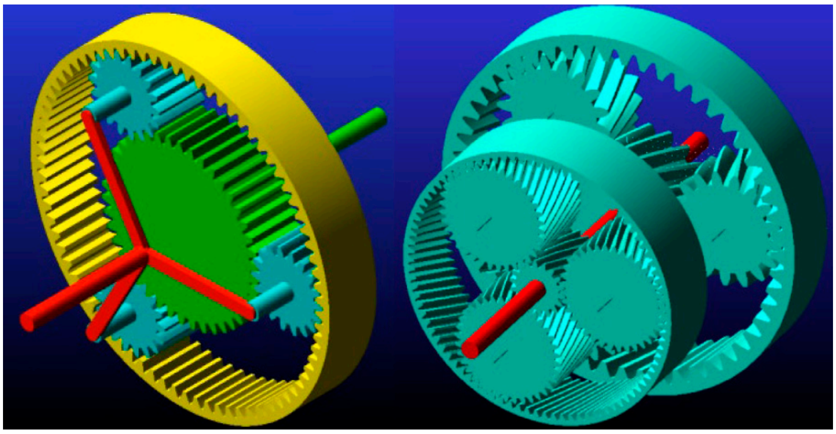

Figure 3. Simplified representation of a multiplier gearbox with two stages.

We have assumed a diameter of the rotor blades of 180 m, a wind speed of 4 m/s at start-up, 12 m/s at nominal wind speed, and 25 m/s at wind turbine shutdown. It is considered that the wind produces the maximum nominal power at a wind speed of 12 m/s, which, depending on the rotor blade, corresponds to a rotor rotation speed of 14 rpm, while the generator rotation speed is of 1500 rpm. For all case studies, we have considered a gearbox with two stages, each with an epicyclic planetary gear train. From the different types of epicyclic geartrains, this study uses the design depicted in Figure 2, because we are interested in the most compact design with the smallest volume solution, in which the operating parameters affecting the gearbox design will be determined. In this design, the input is the planet carrier, the output is the sun, and the ring is fixed. In addition, the pith diameter of the sun is smaller than that of the planets (Table 2). The target for the transmission ratio between the input and output ($i_T = i_1 \cdot i_2$) is around 107, with the transmission ratio for the first and second stages (i_1, and i_2, respectively) being around 10.35. The design of the gearbox and the calculation of load capacity of helical gears have been carried out following the ISO 6336 standard of the International Organization for Standardization [44]. The normalized moduli m_n (mm) used in the optimization procedure are presented in Table 1.

Table 1. Transmission, geometry, and material parameters of the wind turbine gearbox.

Geometry	Values	Transmission	Values	Material	Values
General parameters		Rated Power (P)	7 MW	Material	steel
Normal pressure angle (α_n) Apparent pressure angle (α_t): $\alpha_t = \tan^{-1}(\tan(\alpha_n)/\cos(\beta))$	20° 21.17°	Target transmission rate ($i_T = i_1 \cdot i_2$)	≃107	Density (ρ)	7850 kg/m^3
Normal module range (m_n) Helix angle (β)	10–100 mm 20°	First stage: planetary (i_1) Second stage: planetary (i_2)	≃10.35 ≃10.35	Young's modulus (E)	2.07 × 10^5 MPa
Apparent module (m_t) Tooth width range (b) Addendum factor Dedendum factor	$m_t = m_n/\cos(\beta)$ 10–1000 mm 1 1.25	Normalized moduli (m_n) (mm) used in the optimization procedure	10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 80, 90, 100	Poisson's ratio (ν)	0.29
		Generator rotational speed Optimal rotor speed	1500 rpm 14 rpm	Contact settings	
Sun gear range of variation		Rotor diameter	180 m	Stiffness	1.05 × 10^5 N/mm
Number of teeth (Z_{Sun})	16–60	Driving machine: major shocks Driven machine: uniform operation		Damping coefficient	10
Ring gear range of variation				Exponent	2
Number of teeth (Z_{Ring})	40–400	Planetary gear configuration		Penetration	0.1
		Planet carrier	Input	Friction settings	
Planet gear range of variation		Sun	Output	Static coefficient	1.1
Number of teeth (Z_{Planet})	16–300	Ring	Fixed	Dynamic coefficient	1.0
Number planet gears ($n_{Planets}$)	3			Static velocity	2.0
				Dynamic velocity	5.0

Table 2. Case studies.

Case Study	Tooth Fracture Safety Coefficient (X_F)
1	1.4
2	1.1
3	1.7

The optimization procedure is intended to maximize the tooth fracture safety coefficient (X_F) rather than the gear contact safety coefficient (X_H) based on the ISO standard. This is because this failure tends to be catastrophic and does not generate warning signals before it occurs. In accordance with the standards, the pitch diameter (d_{gear}) of each gear (e.g., sun, planet, or ring gear) is equal to the diameter of the shaft (d_{shaft}) supporting the gear, plus a constant parameter (K_{gear}) (Figure 2), i.e.,:

$$d_{gear} = d_{shaft} + K_{gear} \tag{1}$$

where the parameter K_{gear}, as defined in (Rubio et al., 2023 [14]), is equal to:

$$K_{gear} = 2 \cdot h_1 + 2.5 \cdot m_t + 4 \cdot m_t \tag{2}$$

The parameter d_{shaft} must be adequate to provide the necessary torsional stiffness, while K_{gear} takes into account the apparent gear modulus (m_t), the value of the depth of the keyway in the hub (h_1), and the tooth height [45]. In this sense, the standard establishes that an iteration process must be carried out for gear dimensioning. For a certain material, a standard module for the gear must be chosen. Then, the gear width (b) is obtained for a specific contact safety coefficient. If $X_F < X_H$, a solution with a higher modulus or a material for higher S_{FP}/S_{HP} ratio must be selected. S_{FP} is the allowable bending stress by the material under the geometric and operating conditions of the gear for a given life and with a known level of confidence. S_{HP} is the allowable contact stress by the material under the geometric, operating, and lubrication conditions of the gear for a given life and with a known level of confidence. When a solution that satisfies $X_F > X_H$ is achieved, if

$b > 2{\cdot}d_{gear}$, a material with better characteristics must be selected and the iteration process resumed. Contrary, if $b \ll d_{gear}$ a material with worse characteristics must be selected and the iteration process resumed. Due to the use of simplified procedures to obtain safety coefficients, this method proposed by the standard should not be used in applications subject to extreme speed or load conditions.

Additionally, the tension at the base of the tooth (σ_F) must fulfill that $\sigma_F \leq S_{FP}/X_F$, while the surface pressure on the tooth (σ_H) must satisfy that $\sigma_H \leq S_{HP}/X_H^2$. Both tensions are corrected according to a series of coefficients that allow us to obtain a better approximation to the real tension at the base of the tooth [44].

Eventually, the calculation of the tooth fracture safety coefficient (X_F) by means of the developed optimization framework meets with the ISO standard, and it is imposed on the optimization problem through a constraint that establishes a X_F greater than a certain threshold according to each case study. Other constraints are imposed on the optimization procedure to comply with the standard and the real problem at hand, which are related to the definition of ranges of variation for the tooth width, standard module, the number of teeth, and gear width (Table 1). Additionally, the relationship between the input and output shaft speeds also must fulfilled by the Willis equation for planetary gears. Moreover, several geometrical conditions must be fulfilled for each stage to fulfill the ISO standards [9,43], which encompass:

- The coaxiality condition entails that the number of teeth in the ring is two times the number of teeth of the planet plus the number of teeth of the sun, or in other words, that the diameter of the ring is two times the diameter of the planet plus the diameter of the sun:

$$Z_{ring} = Z_{sun} + 2{\cdot}Z_{planet} \; or \; d_{ring} = d_{sun} + 2{\cdot}d_{planet} \tag{3}$$

- The mounting condition leads to the fact that the number of teeth of the sun plus the ring divided by the number of planets must be a positive integer number:

$$\lambda = \left(Z_{ring} + Z_{sun}\right)/n_{planets} \; with \; \lambda \in \mathbb{N}^{+} \tag{4}$$

- The minimum number of teeth to avoid interference is obtained by means of:

$$Z_{min} = 2{\cdot}\cos\beta/\sin^2(\alpha_t) \tag{5}$$

- The contiguity condition:

$$(\pi/2){\cdot}\Big(\Big(Z_{ring} + Z_{sun}\big)/(Z_{\,planet} + 2{\cdot}\cos(\beta)\Big) > n_{planets}, \text{ with } n_{planets} = 3 \tag{6}$$

- The Willis equation relates angular velocities and number of teeth of different elements of the planetary gear:

$$\frac{\omega_{sun} - \omega_{carrier}}{\omega_{ring} - \omega_{carrier}} = -\frac{Z_{ring}}{Z_{sun}} \tag{7}$$

Furthermore, to define the case studies, real historical data are used to derive reasonable values for certain variables, such as the optimal rotor speed and the forces applied. We have focused on the first stage of the drivetrain as it is the most critical from the point of view of structural integrity and is subject to greater stress. Furthermore, we performed a static analysis, since the structural loads are higher for the starting moment in which the movement begins, and the inertia of the gearbox components must be overcome.

Finally, for all study cases, the aim is to design a gearbox with minimum weight (W) and volume (V), capable of transmitting the nominal power of the wind turbine (P) with a certain transmission ratio (i_T) and a maximum tooth fracture safety coefficient (X_F).

The limitations of this study involve the high computational cost of the high-fidelity models used. Moreover, when dealing with dynamics effects due to the complexity of the problem, the developed multi-objective optimization framework has drawbacks in acquiring data and performing simulations in real-time. However, to the best of the authors' knowledge, there is not currently any digital twin development that solves all these problems satisfactorily. Therefore, the developed platform provides some novelty and presents a step forward in the current literature.

To circumvent these issues, some simplifications are assumed in this research, and in all case studies the developed DT only simulates the running state of the gearbox under the parameters and conditions provided in Table 1, and no real-time data are used. Therefore, the methodology addresses the interaction between the physical WT and the high-fidelity virtual simulations for the digital twin optimization by making use of the offline real historical datasets. The aim is to perform a predictive digital twin training to improve the detection, diagnosis, and monitoring of failures of WT gearboxes. As further research, the digital twin would make use of online real-time data to upgrade the prognostic of the WT gearboxes useful life or time to failure.

Therefore, the critical and complex communication network between the physical WT and the digital layer is beyond the scope of this paper. For that purpose, there are different communication technologies that are both wired and wireless to provide secure, robust, and reliable real-time data [46,47].

4. Results and Discussion

The multi-objective optimization results for the different case studies are presented in Table 3. This table shows the optimal explanatory and response variables from all feasible designs. It is worth noting that a total of 500 designs were evaluated for each case study, in which only the feasible configurations were selected. Unfeasible configurations are those that do not comply with the ISO standard, i.e., those that does not have the minimum number of teeth to avoid interference, and the coaxality, mounting, and contiguity equations (from 3 to 6). Additionally, configurations leading to excessive tooth width, unacceptably high epicyclic train mass, and low compactness are also discarded.

Table 3. Multi-objective optimization results for the different case studies.

Explanatory and Response Variables	Case Study 1 X_F = 1.4	Case Study 2 X_F = 1.1	Case Study 3 X_F = 1.7
Sun number of teeth (Z_{Sun})	35	37	33
Planet number of teeth (Z_{Planet})	151	155	156
Ring number of teeth (Z_{Ring})	337	347	345
Normal module (m_n)	35	30	40
Tooth thickness (b) (mm)	120	151	99
Minimum mass (m) (kg)	10,409	10,217	10,555
Minimum volume (V) (m^3)	1.326	1.301	1.344
Minimum maximum von Mises stress (MPa)	294.32	298.45	292.45
Maximum tooth fracture safety coefficient (X_F)	1.416 > 1.4	1.196 > 1.1	1.714 > 1.7

The proposed multi-objective optimization framework is intended to automatically find the optimal combination of the design variables using high-fidelity models and avoiding carrying out successive iterations of manual simulations. Results provide important conclusions regarding the optimal design of wind turbine gearboxes with the lowest volumes and weight and, therefore, the maximum compactness and power density compared to other designs of epicyclic trains.

For a specific set of mechanical properties of a material, there is a K_{gear} value in the Pareto optimal solution set of the multi-objective optimization problem that minimizes the weight (W), volume (V), compactness (C), and maximum stresses achieved (S) of the epicyclic train by acting on the value of the gear pitch diameter (d_{gear}), the value of the tooth width (b), and the number of teeth of the gears (Z) of the epicyclic gearing. However, there is a trade-off between the competing design variables, since certain combinations of these variables favor the objective of increasing power density without compromising efficiency, while other combinations worsen it.

In this sense, very small values of K_{gear} lead to small gear and pitch diameter, and too large tooth width in order to withstand the stresses generated in the teeth. Then, the strength properties of the material must be improved, otherwise the gear train may experience interference, excessive tooth width, unacceptably high epicyclic train mass, and low compactness. Additionally, the use of small pitch diameters with large modules results in fewer teeth, which causes interference. On the contrary, if the module is reduced the number of teeth increases, overcoming the problem of interference, but the tooth width becomes too large to ensure structural integrity. Therefore, the weight and volume of the gear train is not operational and higher K_{gear} values (and hence, d_{gear} values) must be used. As the value of K_{gear} increases, b decreases at larger pitch diameters and, therefore, lower weights and greater compactness of the planetary gear set are favored. However, the value of K_{gear} cannot be increased freely, since when d_{gear} increases, the volume of the epicyclic train increases as well. As a result, there is a K_{gear} value that minimizes the weight, volume, and compactness of the gears by acting on d_{gear} and b values.

Other issues must be considered, such as b decreasing as the value of m_n increases, and that not all moduli are valid, either because they lead to interference or because b is too large or small (i.e., $b > 2 \cdot d_{gear}$, or $b << d_{gear}$).

Moreover, the larger the d_{gear}, the greater the bending strength at the base of the tooth (σ_F) and surface pressure on the tooth (σ_H). These values exceed the threshold leading to a failure for a given target of fracture and gear contact safety coefficients (e.g., X_F and X_H, respectively) and maximum allowable bending and contact stresses by the material (e.g., S_{FP} and S_{HP}, respectively). These results are in line with previous research from the same authors using analytical equations for the design of the gear train [14].

Considering all the feasible configurations that comply with the ISO standard, which has been obtained by varying the value of K_{gear} and between the normalized modules analyzed (i.e., $m_n \in [10, 100]\ mm$), the variation interval that represents the maximum and minimum values achieved of the target variables are presented in Table 4 (i.e., weight, tooth width, and maximum bending strength at the base of the tooth).

Table 4. Range of variation of the feasible configurations for the target variables: weight (W), tooth width (b), and maximum bending strength at the base of the tooth σ_F).

Variables	Variation Interval
W (kg)	9569–13,844
b (mm)	18–742
σ_F (MPa)	123–312

The wide range of variation in the results obtained for the different configurations compared to the optimized variables, represented in Table 3, demonstrates the worth of the present methodology to obtain an optimized design with maximum power density without compromising efficiency, while maintaining the performance and operability of the wind turbine gearbox. In addition, the developed framework allows us to identify potential failure modes, extend service life and reliability, and reduce maintenance requirements and costs. In this sense, a life cycle and damage analysis, using the Ansys Workbench fatigue tool, has been performed. For a designed infinite life of 1×10^9 cycles and using a zero-based loading option for gear teeth, we have proven that a minimum life of 1×10^6 cycles is achieved for all optimized case studies, so that accumulated damage, defined as the ratio between the designed life and the number of cycles that the critical tooth gear can withstand before failure is 1000. Moreover, it is estimated that premature bearing failure is responsible for a high percentage of all gearbox failures, which depends—among other issues such as improper lubrication—on the axial or radial loads, shaft imbalance and misalignment, which in turn rest on the weight and volume of the gearbox that are minimized in the optimization process, thus reducing the possibilities of failure and allowing to estimate if improper designs may lead to failures.

Eventually, this reasoning supports the idea of the existence of a trade-off between the variables under consideration, which can be easily and automatically assessed using the proposed methodology. Furthermore, the methodology that allows the optimal design of the WT gearbox to support the existing loads with maximum density power can also help to reduce mechanical failures, vibrations, and increase its fatigue life. This is because the selection of non-optimal designs (with greater masses, volumes, and stress levels) can lead to these types of anomalies over time.

5. Conclusions

In conclusion, this study has presented a digital twin-based approach for the multi-objective optimal design of wind turbine gearboxes. The developed optimization framework, utilizing a combination of CAD/CAE tools, enables high-fidelity virtual simulations and the integration of real historical datasets. The methodology allows us to minimize the WT weight, volume, and maximum stresses and strains achieved without compromising efficiency, identify potential failure modes, determine safety factors, and predict fatigue life. The optimization framework deals with gear ratios among stages and planetary gearset geometries and materials, together with the kinematics, dynamics, and the structural integrity of the WT gearbox. Moreover, it enables advanced data analysis for informed decision-making beyond traditional engineering methods.

The results of the case studies conducted demonstrate the usefulness of the developed DT for the accurate modeling and simulation of the WT gearbox, thus allowing us to optimize its design with the aim of maximizing the power density and compactness for enhanced performance and reliability, provide insights into its behavior under diverse operating conditions, and help in the identification of potential failure modes in the gearbox.

This approach presents a promising avenue with the aim to enhance fault diagnosis, health monitoring, diagnosis, analyze variable operation conditions, conduct uncertainty assessment and sensitivity analysis in operating parameters, optimize predictive maintenance, and improve the efficiency of wind turbine gearboxes. Then, the methodology developed can serve as a Decision Support System (DSS) to mitigate downtimes and financial losses associated with wind turbine gearbox failures, ultimately enhancing reliability in wind energy.

Future research endeavors could focus on implementing a high-fidelity prognostic model to forecast the remaining useful life of gearboxes more accurately to overcome certain limitations of this work, including that the methodology should take into account dynamic aspects and conditions that change over time, such as variations in the rotation speed of the blades, as well as critical situations that are reached in the start/stop procedures of wind turbines. Additionally, exploring the integration of real-time data into the digital twin framework could further enhance predictive maintenance strategies and optimize the operational efficiency of wind turbine gearboxes. In this sense, the communication network between the physical wind turbine and the digital layer has not been dealt with in this paper, so this study may not provide a comprehensive overview of the entire digital twin ecosystem. Moreover, the high computational cost associated with the high-fidelity models may hinder the scalability and practical implementation of the digital twin framework in real-world wind turbine operations, especially in large-scale applications.

Author Contributions: Conceptualization, C.L.-A.; methodology, C.L.-A. and F.R.; software, C.L.-A.; validation, C.L.-A. and F.R.; formal analysis, C.L.-A., C.D. and D.G.-H.; investigation, C.L.-A. and F.R.; resources, C.L.-A., C.D. and D.G.-H.; data curation, C.D. and D.G.-H.; writing—original draft preparation, C.L.-A., F.R. and C.D.; writing—review and editing, C.L.-A. and F.R.; visualization, C.D., F.R. and D.G.-H.; supervision, C.L.-A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

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

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