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# Estimating Reliability and Ranking of Wind Turbine Plant under Fuzzy Environment Through Generalized Trapezoidal Fuzzy Numbers (GTFNs)

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**Abstract**
Reliability and ranking estimation of complex systems such as Wind Turbine plant (WTP) is essential for their efficient operation and vulnerability to the operational issues and conditions. Thus, this paper addresses the importance of the reliability assessment of a wind turbine plant incorporating both the routine as well as preventive maintenance strategies using Fuzzy logic. Wind turbines, which are used for the power generation through renewable sources of energy, require effective reliability analysis for the optimal level of performance. For this, generalized trapezoidal fuzzy numbers (GTFNs) are introduced with certain level of confidence. Lambda-Tau methodology together with GTFNs and associated mathematical operations have been employed for calculating the different performance measures e.g. Reliability, Availability, Maintainability, Mean Time to Failure, Mean Time to Repair, Mean Time Between Failure, Expected Number of Failure (ENOF) of the wind turbine plant. Authors also performed ranking analysis for the components of WTP to determine the key components of the same. The outcome of the study can be considered as a valuable reference to the maintenance team to plan strategy in a better way. Based on the results, it can be concluded that this methodology is highly effective for the performance analysis of WTP system. Additionally, the authors have outlined the future scope of the research work at the end of the conclusion section.

**Keywords-** Wind turbine plant, GTFNs, Reliability indices, Lambda-Tau methodology, Ranking, Fault tree.

## 1. Introduction

Reliability analysis is a significant way to understand how the lifecycle of a system's performance behaves. It is a process which monitors the change in reliability measures of a system with respect to time, wear tear out of its different components, maintenance practices and operational conditions. It is therefore important to calculate the different reliability measures of a system to forecast different failures/repairs which leads in a better understanding for planning of some realistic maintenance strategies. On the other hand, sensitivity analysis seeks to establish the level at which the changes of specific components failure impact the overall performance of the system. If one knows how sensitive each component is, in the event of a disturbance it tells what components failure can be manipulated to increase overall reliability. Collectively these analytical tools provide useful recommendations not only on the aspect of reliability.

The use of fuzzy logic in the reliability theory has received a lot of interest in the field of engineering especially in performance analysis of different complex systems (Benhamida et al., 2025; Chachra et al., 2024; Khajuria et al., 2025; Kharola et al., 2022). In recent years many papers published which address the use of different fuzzy methodologies to improve the performance of complex systems. Kumar and Dhiman

(2020) have developed a reliability analysis method based on trapezoidal fuzzy numbers and their operations for transition from point to interval estimate. That is why this approach provide a better understanding of the uncertainty in reliability assessment of the system. However, Dhiman and Kumar (2020) used fuzzy lambda-tau methodology to examine the RAM indices in skim milk powder plant considering human failure and conclude that the human factors/error should be included in reliability models, which is not usually done in practice. In continuation of this, Kumar and Dhiman (2023) proposed an analytical framework for Injection Moulding Machine to quantify the reliability, availability, MTTF, MTTR, MTBF, ENOF by using Right Triangular Generalised Fuzzy Numbers (RTrGFN). The inclusion of RTrGFNs brings a level of assurance into the estimation process as it deals with vagueness in data. Reliability, Availability and Maintainability (RAM) analysis of a screening unit of a paper industry with the help of fuzzy numbers has been done by Garg et al. (2012). The studies adopted Artificial Bee Colony-based Lambda-Tau (ABCBLT) method and conclude that it had a positive impact in minimizing the uncertainty levels related to the RAM parameter.

For wind energy systems, there exist number of works that employed the fuzzy methodologies in order to improve the reliability. Akhtar and Kirmani (2020) used FFTA to assess the reliability of wind energy systems with the help of operational failures and errors by considering them in fuzzy environment. They came up with a fuzzy risk index to enable them to perform an extensive risk analysis and proved that fuzzy logic is efficient in dealing with uncertainties. Aikhuele (2018) proposed a flexible model with the help of the Triangular Intuitionistic Flexibility Ranking and Aggregating (TIFRA) operator for failure detection and reliability management of wind turbines where the primary focus was on the areas of failure and the researchers described the faults in the system in detail. Gao et al. (2018) analysed fuzzy reliability through universal generating function by considering failure dependence, multiple load effects and strength degradation. These dynamic models made a substantial development in the calculation of the system reliability. This approach was later expanded by Huang et al. (2021) to evaluate the reliability of doubly fed induction generators in wind turbine systems. The integration of fuzzy numbers in unfolding system's states improved the reliability especially for those systems that described the components using trapezoidal fuzzy numbers. Ali et al. (2023) suggested a fault tree analysis technique integrated with the log-linear proportional intensity model to optimize failure probability, failure rate and mean time to failure of wind turbines. This method helped to identify the components which were most affected by the poor repair quality and to define preventive maintenance actions.

In recent years, various method proposed to enhance the reliability and performance of networks and systems. Joshi et al. (2022) proposed a Markov-based mathematical model for a P2P network to evaluate availability, reliability, and MTTF And identified critical components. Ram et al. (2024b) introduced a Programmable Logic Controller (PLC) based system and its reliability is computed from universal generating function technique. In the realm of stochastic-flow networks, Forghani-Elahabad and Mahdavi-Amiri (2013) proposed a simple algorithm for finding all minimal path vectors in stochastic-flow networks and demonstrated that this algorithm more efficient than the existing algorithm. Forghani-Elahabad (2021) discussed the key exact methods for evaluating the reliability of multistate flow networks (MFNs) using minimal cuts (MCs) and minimal paths (MPs). Expanding on this work, Forghani-Elahabad (2022) examined the quickest path reliability problem and the reliability of two and k disjoint minimal paths (DMPs), presenting algorithms with benchmark examples and their complexity analyses. It also introduces related optimization problems for finding the most reliable DMPs.

In literature researchers has also discussed safety and failure prediction techniques in wind turbine. Parthasarathy and Narayanan (2014) pointed out that safety engineering is crucial for large-scale wind turbines and introduced the basic analysis methods for assessing the safety of the same. Xiao et al. (2019)

employed radar charts and support vector machines for fault prediction in wind turbines with a high accuracy. Zhu et al. (2019) proposed a method based on fuzzy synthesis for the real-time evaluation of wind turbine gearbox conditions, the proposed method give higher accuracy in determining the operating state and possible failure for gear box of the turbine. Li et al. (2022) proposed an advanced FMEA method for the offshore wind turbines based on the large amount of data analysis and suggest optimal strategies to system engineers to avoid the failure and improve its performance. On the other hand, Hosseini et al. (2022) provide application of fuzzy logic in pitch angle control for a wind turbine to improve power system oscillation and found that the fuzzy controller minimizes the power oscillation and optimizes the turbine dynamic. Other studies like Li et al. (2020) investigated the reliability of the wind turbines, including control strategies and environmental factors, by using the survival signature and FMEA. A new FMEA approach based on the fuzzy MCDM technique with spherical fuzzy sets was suggested by Ghoushchi et al. (2022). Kang et al. (2019) worked on the reliability assessment of the FOWT by performing the FTA to assess the risk of failure due to marine environment and determine the main causes of Failure for the same. In recent research, Rezamand et al. (2019) have proposed an analysis of wind turbine generator reliability, based on the different life data analyses, for optimizing the effect of the electrical loads on reliability. Liu et al. (2023) have proposed fatigue reliability assessment method based on continuous time Bayesian network and FEA.and its performance is verified by a comprehensive analysis with the results of discrete time Bayesian networks. Later on, Ram et al. (2024a) focused on evaluating the reliability of a wind turbine drive system under three repair policies using analytical methods applicable to any maintainable system. A bivariate stochastic process with a copula function is proposed for modelling repairs, and the Markov approach with the supplementary variable technique is used for time-dependent reliability and failure analysis. Furthermore, Gaidai et al. (2024) apply bivariate modified Weibull method to assess extreme operational loads on a 10-MW floating wind turbine's drivetrain, considering cross-correlated forces and environmental effects.

**Table 1.** Related work review.

| References | Objectives | Area | Methodology | Solution algorithm |
|---|---|---|---|---|
| Dhiman and Kumar (2020) | Investigated RAM indices in skim milk powder plant with human mistakes. | Industrial system reliability | Fuzzy lambda-tau methodology | Arithmetic operations on fuzzy numbers |
| Kumar and Dhiman (2023) | Analysis of reliability, availability, MTTF, MTTR, MTBF, and ENOF for an injection moulding machine. | Manufacturing system reliability | Right triangular generalized fuzzy numbers (RTrGFN) | Fuzzy arithmetic with confidence level |
| Akhtar and Kirmani (2020) | Evaluates the reliability of wind energy systems, integrating operational failures and errors. | Wind energy systems | Fuzzy fault tree analysis (FTA) | Fuzzy risk index for risk analysis |
| Gao et al. (2018) | Explores fuzzy reliability models for multistate systems using UGF. | Multi-state systems (wind turbines) | Fuzzy universal generating function (FUGF) | Dynamic modeling using UGF |
| Huang et al. (2021) | Assesses the reliability of doubly fed induction generators in wind turbine systems. | Wind turbine systems | Fuzzy universal generating function (FUGF) with trapezoidal fuzzy numbers | Multi-state system (MSS) assessment |
| Ali et al. (2023) | Improves failure probability, failure rate, and MTTF for wind turbines with imperfect repairs. | Wind turbines | Fault tree analysis (FTA) with log-linear proportional intensity model (LPIM) | Preventive maintenance planning |
| Asghari et al. (2015) | Comparative analysis of static and dynamic fault tree models for wind turbine systems. | Wind turbine systems | Static fault tree (SFT) and dynamic fault tree (DFT) | Monte carlo simulation for DFT |
| Kang et al. (2019) | Evaluates reliability and failure of floating offshore wind turbines. | Floating offshore wind turbines | Fault tree analysis (FTA) | Risk assessment of marine conditions |
| Li et al. (2022) | Provides recommendations for offshore wind turbine design to prevent failures. | Offshore wind turbines | Improved FMEA based on extensive data analysis | Specialist knowledge integration |
| **Presented work** | **Performance analysis and ranking of different components of a wind turbine plant.** | **Wind turbine plant** | **Generalized trapezoidal fuzzy number** | **Lambda-tau methodology and ranking** |

Based on the literature review it is evident that, despite a decent progress made in reliability analysis, through different approaches, for complex systems such as wind turbines, there is still a need of combining the fuzzy logic with the conventional reliability analysis. More work has to be done to develop these models and to generalize them to other industrial fields in order to provide effective reliability predictions under uncertainty.

To clearly define the focus of the present study, the authors have summarized the related work on fuzzy reliability, along with the corresponding solution approaches, in **Table 1**.

### 1.1 Area of Further Investigation

The authors have conducted a critical review of previous research and found that the

- Existing studies lack a combined analysis of both regular and preventive maintenance strategies in wind turbine reliability assessment.
- limited work is reported for the modelling of wind turbine plant application through Trapezoidal Fuzzy Numbers (TFN).
- Comprehensive analysis for a wind turbine plant is needed to evaluate the performance behaviour, and ranking of the same.
- The Lambda-Tau methodology is underutilized in the fuzzy reliability analysis of wind turbine systems.

Keeping the above point in mind here author proposed a novel study which is focused to integrate fuzzy modelling, performance evaluation, and both maintenance strategies for wind turbines plant using fault tree analysis, TFN and Lambda-Tau methodology to evaluate different reliability measures for the same. In this paper author introduces a new method for assessing the reliability and ranking of wind turbine plants using fuzzy numbers (GTFNs) and the Lambda-Tau methodology. This method offers a more reliable and adaptable framework for wind turbine plants compared to traditional methods. The main reason for using this framework is to handle the uncertainty in real data from wind turbine systems. Traditional methods use fixed numbers, but in real life, the data is not always exact. So, we used GTFNs with the Lambda-Tau methodology, To better model reliability under uncertain conditions.

The paper is structured as follows: Section 2 provides a description of the wind turbine plant. Section 3 presents the nomenclature used throughout the paper. Section 4 introduces the fault tree of the wind turbine plant. Section 5 outlines the proposed methodology. Section 6 discusses the computational analysis. Section 7 explains the solution methodology, while Section 8 presents the results and discussion. Finally, Section 9 concludes the paper by summarizing the key findings.

## 2. Description of a Wind Turbine Plant

A wind turbine plant is a vital technology harnessing renewable wind energy to generate electricity. Interconnected components seamlessly transform kinetic wind energy into electrical energy. Understanding each component's role optimizes performance and ensures reliability of a wind turbine plant. The Wind Turbine plant contains the following main components. (Refer **Figure 1**).

***Blades*:** The aerodynamically shaped blades primarily capture wind energy, efficiently converting its rotational kinetic energy into mechanical motion. Blade efficiency directly impacts overall output, so proper design enhances energy harvesting.

***Pitch system*:** It adjusts blade angles to control rotational speed and optimize energy capture. By altering pitch, it handles varying winds, ensuring efficient, safe operation.

***Hub*:** It connects blades to the main shaft, playing a crucial role in transmitting the mechanical energy to the gearbox.

***Gearbox*:** The gearbox is vital for increasing the rotational speed from the low-speed shaft, which is attached to the blades, to the high-speed shaft, which is connected to the generator. It contains two main subcomponents as bearing and gears. Bearings take the load lessen friction and make sure the internal parts spin smoothly and last longer. Gears amplify the leisurely rhythms of the spinning blades to the quick paces compelling the generator. In synchronizing speed and torque, they are the key to transforming one kind of motion into another, converting the sweeping rotations atop into the pulsing currents that flow from the stalk.

***Brake*****:** The brake in a wind turbine is a mechanical component which is connected to the high-speed shaft that helps reduce rotational speed or stop the turbine in emergencies. Wind turbines are designed not to operate above certain wind speeds to prevent damage from strong winds and excessive loads. A disc brake can be activated in three ways: mechanically, electrically, or hydraulically. This allows the rotor to be stopped safely during emergencies, maintenance, or when it exceeds a set speed threshold.

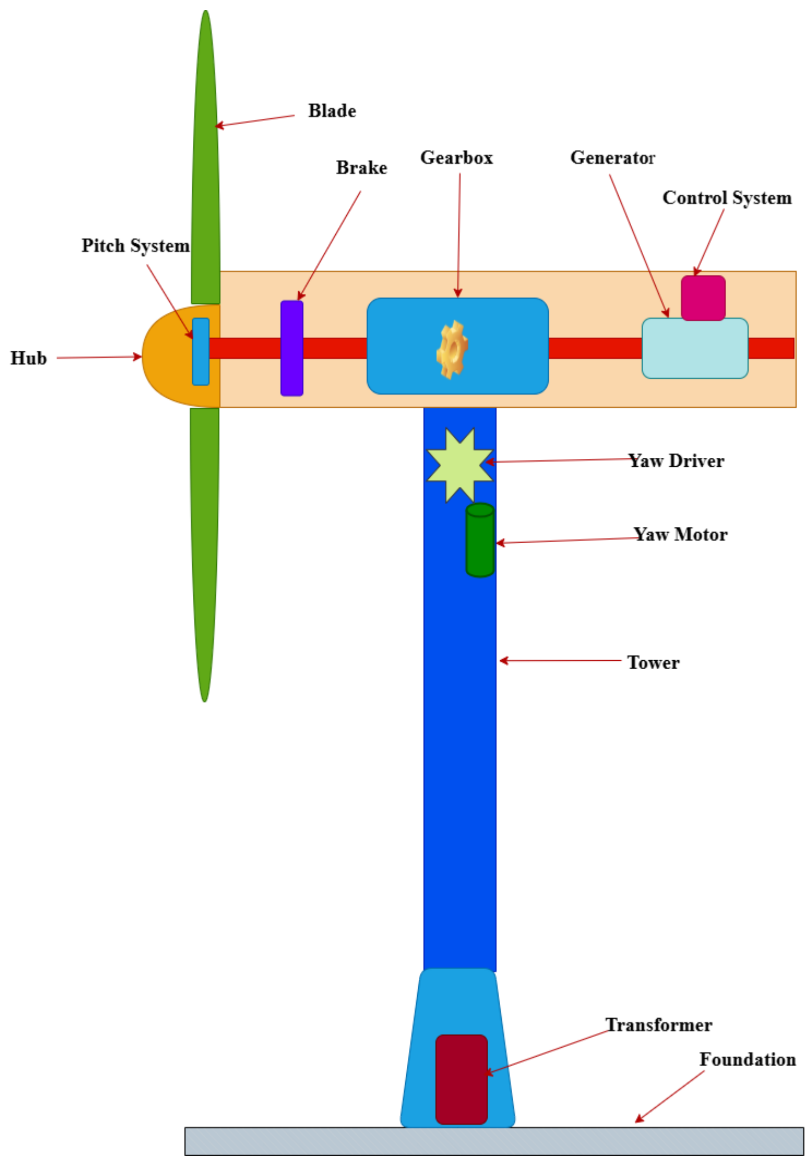


**Figure 1.** Structure of a wind turbine.

***Generator*:** A wind turbine's generator transforms the rotor's mechanical energy into electrical energy. The most common types of generators used are induction generators (IGs), doubly fed induction generators (DFIGs), and permanent magnet synchronous generators (PMSGs). Permanent magnet generators are more efficient and require less maintenance compared to induction generators, but they are also more expensive. Most wind turbines use either a permanent magnet generator or an induction generator for power generation.
***Control system*:** The control system is the brain of the wind turbine. It constantly checks the turbine's condition to ensure everything is working properly. The controller adjusts the pitch of the blades and the direction of the yaw system to capture the most power from the wind. This helps the turbine operate efficiently and safely.
***Yaw system*:** The yaw system rotates the turbine to face the wind direction, optimizing energy capture. It consists of two main subcomponents which are yaw driver and yaw motor. Yaw driver rotates the entire turbine nacelle to align it with the wind direction, ensuring optimal energy capture while yaw motor provides the necessary force to rotate the yaw system.
***Transformer*:** In a wind turbine, transformers adjust the electrical voltage. They take in AC power at a certain voltage and adjust it according to their requirements. In order to lower power losses during long-distance transmission, a step-up transformer increases voltage. Transformers decrease the voltage when power enters a community, ensuring that homes and other structures are safe. This guarantees that everyone can use the electricity efficiently.
***Tower*:** A wind turbine's tower generally consists of tubular or lattice-shaped galvanized steel, though some parts may also be built of concrete. It supports the rotor, nacelle, blades, and other wind turbine equipment. Tower heights are typically equivalent to the rotor's diameter, guaranteeing that the turbine can capture the best wind speeds for producing electricity.

## 2.1 Common Faults in Wind Turbine Plant

Wind turbine plant is made up of different parts and each of these parts can experience some faults which in turn have an impact on the performance of the turbine as well as the amount of power generated. Listed below are some of the possible faults of each component, their source, and effects on the operation of the system.
***Blades*:** Failure of blades is caused by fatigue of the used material, severe weather conditions, and manufacturing imperfections. When blades fail, the rotor ends up being off balance and this means that the efficiency is lowered and if the failure is huge then there could be severe structural damage.
***Pitch system*:** Some of the difficulties occurring in the pitch system are as a result of hydraulic faults, electrical issues or mechanical damage. If the pitch system does not respond, the blades cannot change the angle of the power that they deliver and this means that less power is being transferred.
***Hub*:** Fatigue due to varying stresses in material and poor fastening during assembly often results to formation of cracks in the turbine hubs, which is an indication of mechanical divisions. If the blades detach from such failures, the rotor and other internal parts will receive many damages to break energy production.
***Gearbox*:** Gearbox failure in wind turbines can be caused by multiple factors. High loads from changing wind speeds, direction shifts, and turbulence put stress on gearbox components. Continuous use leads to wear and tear on subcomponents, such as gears and bearings. A lack of proper lubrication can result in overheating and damage to these components. Poor maintenance can allow small issues to escalate into major problems, eventually leading to gearbox failure.
***Brakes*:** Some of the brake malfunctions caused by wearing reducing friction pads, hydraulic leaks draining line pressure, or mechanical defects in sliding parts occur frequently.
***Generator*:** Some electrical faults interrupt the flow of current, other faults allow current to flow through an insulation, and high temperatures beyond the tolerance level often lead to the breakdown of a generator. A troubled generator is one that results in loss of output.
***Control system*:** Discrepancies in a control system can be due to software issues, problem with sensor, or

communication issues. In the event that the control system is not functioning as expected, there is a possibility that the turbine will not be operating as it should, or not operate at all, thus, cutting down on production and putting pressure on other components.

***Yaw system***: Mechanical wear on the yaw driver/motor often leads to yaw system failures. Problems associated with the yaw motor or driver cause improper wind-alignment as well as inefficiency and additional structural stress due to the improper alignment of the wind.

***Transformer***: Common root-causes of transformers comprise of insulation breakdowns, overheating, and electrical troubles. An inadequate transformer reduces the efficiency of conversion to the grid level, thus the turbine system's performance is affected.

***Tower***: Despite such rarity, tower failures can arise from structural fatigue, problems with the foundation or adverse weather conditions. This would result into the complete destruction of the wind turbine since the tower would collapse leading to high level of harm and risks.

Any of these malfunctions can significantly affect the performance of a turbine, reduce efficiency, increase maintenance costs and even pose a risk to safety.

## 3. Nomenclature

**Table 2** provides the definitions of the symbols, which retain their conventional meanings and are consistently used throughout the paper.

**Table 2.** Nomenclature.

| Symbols | Description |
|---|---|
| $\Omega$ | Level of confidence |
| $\omega_{\min}$ | lowest of all $\omega$ |
| $\lambda_{\text{Component}}$ | Failure rate of each component |
| $\tau_{\text{Component}}$ | Repair time of each component |
| $\lambda_{\text{WT}}$ | Failure rate of wind turbine |
| $\tau_{\text{WT}}$ | Repair time of wind turbine |
| $R_{WT}$ | Reliability of wind turbine |
| MTTF | Mean time to failure |
| MTTR | Mean time to repair |
| MTBF | Mean time between failures |
| $A_{WT}$ | Availability of the wind turbine system |
| $M_{WT}$ | Maintainability of the wind turbine system |
| ENOF | Expected number of failures |
| $\lambda_{BL}/\lambda_{PS}/\lambda_{H}/\lambda_{BE}/\lambda_{G}/\lambda_{BR}\lambda_{GE}/\lambda_{CS}/\lambda_{YD}/\lambda_{YM}/\lambda_{TR}/\lambda_{TO}$ | Failure rate of blade/ Pitch system/ Hub/ Bearing/ Gear/ Brake/ Generator/ Control system/ Yaw Driver/ Yaw motor/ Transformer/ Tower |
| $\lambda_{BL}/\lambda_{PS}/\lambda_{H}/\lambda_{BE}/\lambda_{G}/\lambda_{BR}\lambda_{GE}/\lambda_{CS}/\lambda_{YD}/\lambda_{YM}/\lambda_{TR}/\lambda_{TO}$ | Repair time of blade/ Pitch system/ Hub/ Bearing/ Gear/ Brake/ Generator/ Control system/ Yaw driver/ Yaw motor/ Transformer/ Tower |

## 4. Fault Tree for Wind Turbine Plant

The main components of a wind turbine plant are the Blade, Pitch system, Hub, and Gearbox, which includes the subcomponents Bearing and Gear, along with the Brake, Generator, Control system, and Yaw system, which consists of the subcomponents Yaw driver and Yaw motor, as well as the Transformer and Tower. All these components are interconnected in a series system, meaning the failure of any single component leads to the failure of the entire system. Considering their interconnection in the overall performance of a wind turbine plant (WTP), the author has developed a fault tree for the wind turbine system, as shown in **Figure 2**.

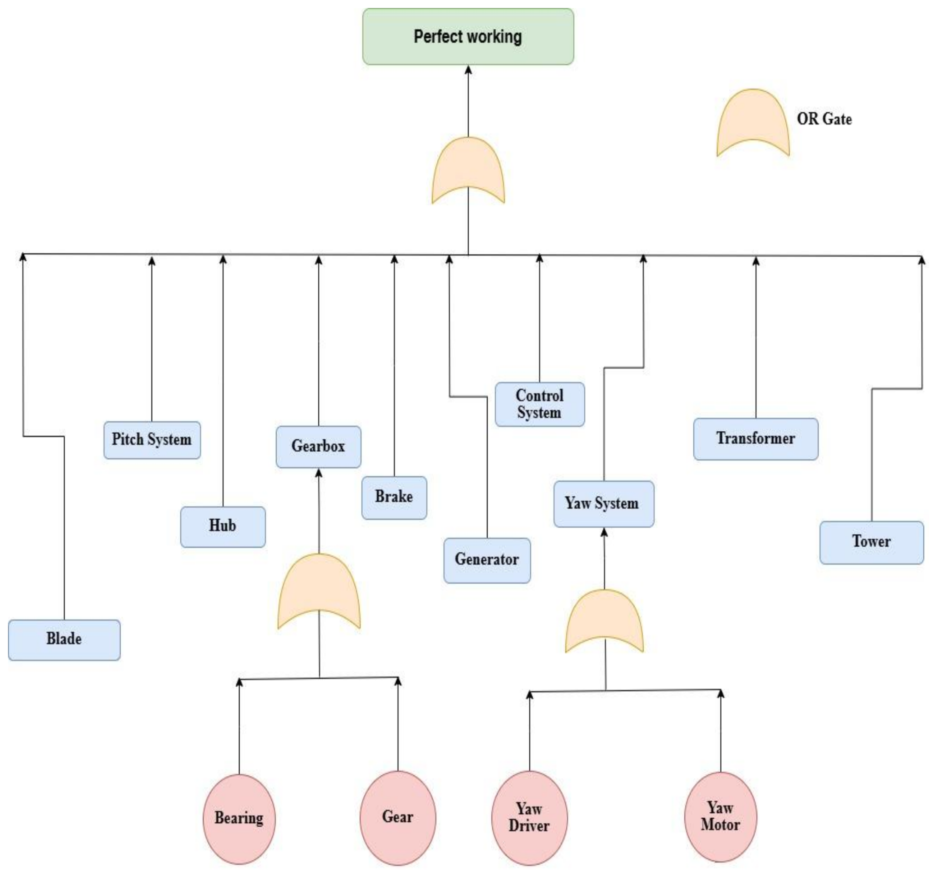


**Figure 2.** Fault tree diagram of WTP.

## 5. Proposed Methodology

In this study, Generalized Trapezoidal Fuzzy Numbers (GTFNs) are used to model uncertainty in failure and repair data because it is modest to apply and easy to understand. Our main aim was to handle uncertainty in failure and repair data of the wind turbine system without making the model too complicated. Methods like intuitionistic fuzzy, neuromorphic fuzzy, or picture fuzzy involve extra parameters, which were not necessary for our study. GTFNs allowed us to manage uncertainty effectively and perform reliability and ranking analysis in an easier way.

### 5.1 Generalized Trapezoidal Fuzzy Number

A fuzzy number $\tilde{F} = \langle(\delta_1, \delta_2, \delta_3, \delta_4; \omega), \delta_i \in R\rangle$ is said to be the generalized trapezoidal fuzzy number if the following properties are satisfied by the membership function.

- $\tilde{F}$ is continuous function.
- $\tilde{F}$ is zero for all $x \in (-\infty, \delta_1) \cup (\delta_4, \infty)$.
- $\tilde{F}$ is strictictly increasing on $[\delta_1, \delta_2]$ and strictictly decreasing on $[\delta_3, \delta_4]$.
- $\mu_{\tilde{F}}(x) = \omega$ for all $x \in [\delta_2, \delta_3]$ where $0 < \omega \leq 1$.

If $\omega = 1$, then it is a normal fuzzy number otherwise generalized trapezoidal fuzzy number.

With the membership function as, its graphical representation is given in **Figure 3**.

$$\mu_{\tilde{F}}(x) = \begin{cases} \left(\frac{x-\delta_1}{\delta_2-\delta_1}\right)\omega\ ;\ \delta_1 \le x < \delta_2 \\ \omega\ ;\ \delta_2 \le x < \delta_3 \\ \left(\frac{\delta_4-x}{\delta_4-\delta_3}\right)\omega\ ;\delta_3 \le x < \delta_4 \\ 0\ ; \quad \text{otherwise} \end{cases}$$

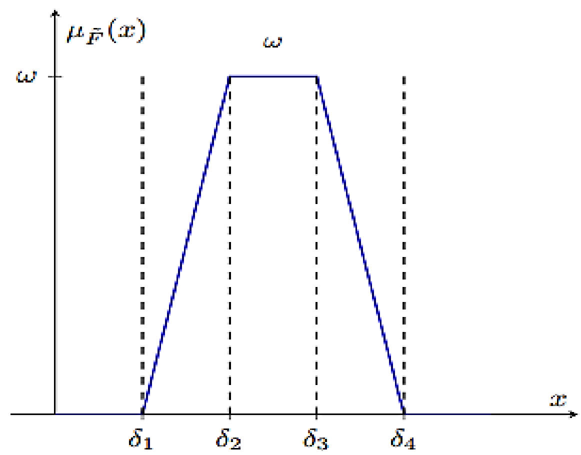


**Figure 3.** Generalized Trapezoidal fuzzy number.

### 5.2 Alpha-Cut

The alpha-cut of the generalized trapezoidal fuzzy number $\tilde{F}$ =($\delta_1, \delta_2, \delta_3, \delta_4$;$\omega$) is the closed interval.

$$\tilde{F} = \left[\tilde{F}^{(L)}_{(\alpha)}, \tilde{F}^{(R)}_{(\alpha)}\right] = \left[\delta_1 + \frac{\alpha}{\omega}(\delta_2 - \delta_1)\,, \delta_4 - \frac{\alpha}{\omega}(\delta_4 - \delta_3)\right]\ \alpha \in [0, \omega] \tag{1}$$

Its graphical representation is given in **Figure 4**.

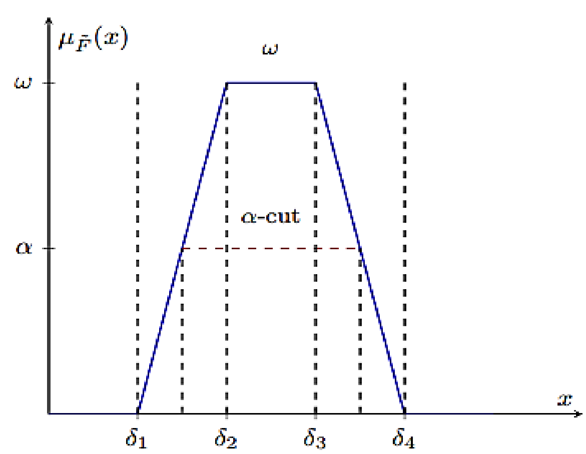


**Figure 4.** Pictorial representation of alpha-cut of GTFN.

### 5.3 Fuzzy Arithmetic Operations for Generalized Trapezoidal Fuzzy Number

In this section, we discuss four operations (addition, subtraction, multiplication, and division) for two generalized trapezoidal fuzzy numbers using the alpha-cut method (interval method) (Mukherjee et al., 2023).

Suppose $\widetilde{F_1}$ =$(\delta_1, \delta_2, \delta_3, \delta_4;\omega_1)$ and $\widetilde{F_2}$ =$(\eta_1, \eta_2, \eta_3, \eta_4;\omega_2)$ be two generalized trapezoidal fuzzy numbers with different levels of satisfaction $\omega_1$ and $\omega_2$ where $0 \leq \omega_1 < \omega_2 \leq 1$ then $\omega$-cut of the fuzzy number $\tilde{F}_1$ and $\tilde{F}_2$ Transforms into new generalized trapezoidal fuzzy numbers $\tilde{F_1}^*$ and $\tilde{F_2}^*$ as follows

$\widetilde{F_1}^* = (\delta_1, \delta_2^*, \delta_3^*, \delta_4;\omega_1) = (\delta_1, \delta_2, \delta_2, \delta_4;\omega_1) = \widetilde{F_1}$ and $\widetilde{F_2}^* = (\eta_1, \eta_2^*, \eta_3^*, \eta_4;\omega_2)$

where, $\delta_2^* = \delta_1 + \omega_{min}\left(\frac{\delta_2-\delta_1}{\omega_1}\right) = \delta_2$ and $\delta_3^* = \delta_3 - \omega_{min}\left(\frac{\delta_3-\delta_2}{\omega_1}\right) = \delta_2$,
$\eta_2^* = \eta_1 + \omega_{min}\left(\frac{\eta_2-\eta_1}{\omega_1}\right)$ ,$\eta_3^* = \eta_4 - \omega_{min}\left(\frac{\eta_4-\eta_3}{\omega_1}\right)$.

#### 5.3.1 Addition

Suppose $\widetilde{F_1}^*$ =$(\delta_1, \delta_2^*, \delta_3^*, \delta_4;\omega_1)$ and $\widetilde{F_2}^*$ =$(\eta_1, \eta_2^*, \eta_3^*, \eta_4;\omega_2)$ then addition of two generalized trapezoidal fuzzy numbers with two distinct confidence level generates a generalized trapezoidal fuzzy number and defined by

$\widetilde{F_1}^* + \widetilde{F_2}^* = (\delta_1 + \eta_1, \delta_2^* + \eta_2^*, \delta_3^* + \eta_3^*,, \delta_4 + \eta_4;\omega_1)$.

#### 5.3.2 Subtraction

Suppose $\widetilde{F_1}^* = (\delta_1, \delta_2^*, \delta_3^*, \delta_4;\omega_1)$ and $\widetilde{F_2}^* = (\eta_1, \eta_2^*, \eta_3^*, \eta_4;\omega_2)$ then subtraction of two generalized trapezoidal fuzzy numbers with two distinct confidence level generates a generalized trapezoidal fuzzy number and defined by

$\widetilde{F_1}^* - \widetilde{F_2}^* = (\delta_1 - \eta_4, \delta_2^* - \eta_3^*, \delta_3^* - \eta_2^*,, \delta_4 - \eta_3;\omega_1)$.

#### 5.3.3 Multiplication

Suppose $\widetilde{F_1}^* = (\delta_1, \delta_2^*, \delta_3^*, \delta_4;\omega_1)$ and $\widetilde{F_2}^* = (\eta_1, \eta_2^*, \eta_3^*, \eta_4;\omega_2)$ then multiplication of two generalized trapezoidal fuzzy numbers with two distinct confidence level generates a generalized trapezoidal fuzzy number and defined by

$\widetilde{F_1}^* \times \widetilde{F_2}^* = (\delta_1 \times \eta_1, \delta_2^* \times \eta_2^*, \delta_3^* \times \eta_3^*,, \delta_4 \times \eta_4;\omega_1)$, if $\delta_1, \delta_2^*, \delta_3^*, \delta_4, \eta_1, \eta_2^*, \eta_3^*, \eta_4$ are all positive real numbers.

#### 5.3.4 Division

Suppose $\widetilde{F_1}^* = (\delta_1, \delta_2^*, \delta_3^*, \delta_4;\omega_1)$ and $\widetilde{F_2}^* = (\eta_1, \eta_2^*, \eta_3^*, \eta_4;\omega_2)$ then division of two generalized trapezoidal fuzzy numbers with two distinct confidence level generates a generalized trapezoidal fuzzy number and defined by

$\frac{\widetilde{F_1}^*}{\widetilde{F_2}^*} = \left(\frac{\delta_1}{\eta_4}, \frac{\delta_2}{\eta_3^*}, \frac{\delta_3}{\eta_2^*}, \frac{\delta_4}{\eta_1}, \omega_1\right)$, if $\delta_1, \delta_2^*, \delta_3^*, \delta_4, \eta_1, \eta_2^*, \eta_3^*, \eta_4$ are all nonzero positive real numbers.

### 5.4 Defuzzification

Defuzzification is the process which converts the fuzzified values back into a crisp value. In certain scenarios, the output of a fuzzy process needs to be represented as a precise single value rather than a fuzzy set. Defuzzification transforms a fuzzy quantity into a specific value, much like fuzzification converts a precise value into a fuzzy set. There are different ways to defuzzify data. Some common methods include the mean area method, weighted average method, maximum membership degree, and centroid method. The best method depends on the problem and its specific requirements, like accuracy, computational efficiency, and easier for understanding. The centroid method is the most common and useful for real-world problems because it finds a balanced result by averaging all possible values in the fuzzy set.

Defuzzification of a generalized trapezoidal fuzzy number $\widetilde{F_1} = (\delta_1, \delta_2, \delta_3, \delta_4; \omega_1)$ is denoted by $d^*$and is defined by $d^* = \frac{\delta_1+\delta_2+\delta_3+\delta_4}{4}$.

### 5.5 Ranking of the Component of the Wind Turbine System

Ranking is one of the system's performance measures, which give insight about the critical component of the system in terms of their significant contribution in overall performance of the system. It is a comprehensive approach which help us to rank the different component of a complex system in which they needed the attention from maintenance team. This method was implemented by Tanaka et al. (1983) to rank the different parts of the system depending on their impact on the system's overall performance. Later on, (Dhiman and Kumar, 2020; Kumar and Dhiman, 2023) extend this method to various industrial system using Right triangular generalized fuzzy number. The method has been extended for wind turbines in the present study using generalized trapezoidal fuzzy numbers.

Failure rate of wind turbine system $\lambda_{WT}$ is defined as a generalized trapezoidal fuzzy number as:

$\lambda_{WT} = \lambda_{WT}(\lambda_{Component,}\tau_{Component}) = (\lambda_{x_1}, \lambda_{x_2}, \lambda_{x_3}, \lambda_{x_4})$ represents the fuzzy value of the failure rate of the wind turbine system.

$\lambda_{Componet} = (\lambda_{c_1}, \lambda_{c_2}, \lambda_{c_3}, \lambda_{c_4})$ represents the fuzzy value of the failure rate of component of the wind turbine system.

$$V(\lambda_{WT}, \lambda_{Component}) = (\lambda_{x_1} - \lambda_{c_1}, \lambda_{x_2} - \lambda_{c_2}, \lambda_{x_3} - \lambda_{c_3}, \lambda_{x_4} - \lambda_{c_4}) \tag{2}$$

This expression indicates the magnitude of the wind turbine system improvement.

$$R(\lambda_{WT}, \lambda_{Component\ 1}) > R(\lambda_{WT}, \lambda_{Component\ 2}) \tag{3}$$

### 5.6 Research Framework

To visualize the steps involved in this study, a research framework diagram is provided below in **Figure 5**. The diagram provides an overview of the process, process start with the modelling of the Wind Turbine Plant (WTP), followed by the use of Generalized Trapezoidal Fuzzy Numbers (GTFNs) for the fuzzification process. After that, the centroid method will be used for defuzzification, the application of the Lambda-Tau methodology to assess different reliability and performance measures, and ending with the ranking of the WTP components.

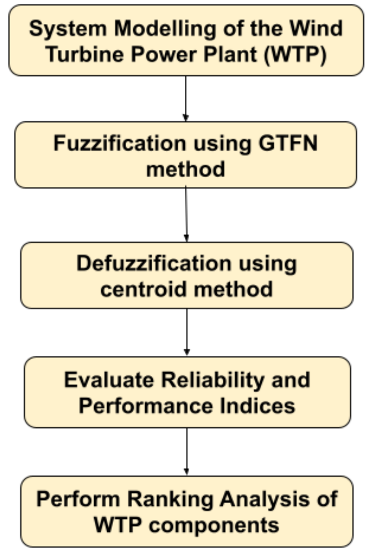


**Figure 5.** Research framework diagram.

## 6. Computational Analysis

### 6.1 Data Acquisition

Author have gone through the various literature for understanding the nature of different components failure rate and the failure/repair data rate for each component were taken from the Santos et al. (2014) along with some expert opinions. Following **Table 3** provides an overview of the recorded values for each component.

**Table 3.** Crisp values of the failure and repair rate of components.

| Components | Failure rate per year | Failure rate per hour ($\lambda$) | Repair time in hours ($\tau$) |
|---|---|---|---|
| Blade | 1.48 | 0.0001689 | 8 |
| Pitch system | 0.08 | 0.0000091 | 5 |
| Hub | 0.185 | 0.0000211 | 4 |
| Gearbox bearing | 0.07 | 0.0000080 | 6 |
| Gearbox gear | 0.05 | 0.0000057 | 8 |
| Brake | 0.04 | 0.0000046 | 2 |
| Generator | 0.08 | 0.0000091 | 4 |
| Control system | 0.24 | 0.0000274 | 4 |
| Yaw system yaw driver | 0.02 | 0.0000023 | 4 |
| Yaw system yaw motor | 0.03 | 0.0000034 | 5 |
| Transformer | 0.02 | 0.0000023 | 5 |
| Tower | 0.19 | 0.0000217 | 8 |

### 6.2 Component wise Fuzzified Data

To convert component failure rate and repair rate from crisp to fuzzy using GTFN, there is no specific criterion; it depends on the uncertainty and variability in the data. Typically, tolerance levels are chosen based on expert opinions or historical failure data. For a Wind Turbine Plant, the tolerance level can range from 10% to 30%. For a moderate level of variability in data, this paper considers a 15% tolerance level.

The data is fuzzified in this stage by using a 15% bilateral tolerance on both sides.

At this stage fuzzified values of $\lambda$ and $\tau$ are represented as $(\lambda - 15\%, \lambda, \lambda + 15\%)$ and $(\tau - 15\%, \tau, \tau + 15\%)$ respectively and the crisp parameters are transformed into fuzzy parameters using the conversion method mentioned above, and some weight has been assigned as shown in **Table 4**.

**Table 4.** Fuzzified values of the parameters of components.

| Failure rate($\lambda$) (in hrs.) | Repair time ($\tau$) (in hrs.) | Weightage $\omega_{min}$ |
|---|---|---|
| $\lambda_{BL} = (0.000144, 0.000169, 0.000194, 0.8)$ | $\tau_{BL} = (6.8, 8, 9.2, 0.8)$ | 0.8 |
| $\lambda_{PS} = (0.000008, 0.000009, 0.000011, 0.85)$ | $\tau_{PS} = (4.25, 5, 5.75, 0.85)$ | 0.85 |
| $\lambda_{H} = (0.000018, 0.000021, 0.000024, 0.9)$ | $\tau_{H} = (3.4, 4, 4.6, 0.9)$ | 0.9 |
| $\lambda_{GB} = (0.000007, 0.000008, 0.000009, 0.8)$ | $\tau_{GB} = (5.1, 6, 6.9, 0.8)$ | 0.8 |
| $\lambda_{G} = (0.000005, 0.000006, 0.000007, 0.8)$ | $\tau_{G} = (6.8, 8, 9.2, 0.8)$ | 0.8 |
| $\lambda_{BR} = (0.000004, 0.000005, 0.000005, 0.85)$ | $\tau_{BR} = (1.7, 2, 2.3, 0.85)$ | 0.85 |
| $\lambda_{GE} = (0.000008, 0.000009, 0.000011, 0.85)$ | $\tau_{GE} = (3.4, 4, 4.6, 0.85)$ | 0.85 |
| $\lambda_{CS} = (0.000023, 0.000027, 0.000032, 0.85)$ | $\tau_{CS} = (3.4, 4, 4.6, 0.85)$ | 0.85 |
| $\lambda_{YD} = (0.000002, 0.000002, 0.000003, 0.85)$ | $\tau_{YD} = (3.4, 4, 4.6, 0.85)$ | 0.85 |
| $\lambda_{YM} = (0.000003, 0.000003, 0.000004, 0.8)$ | $\tau_{YM} = (4.25, 5, 5.75, 0.8)$ | 0.8 |
| $\lambda_{TR} = (0.000002, 0.000002, 0.000003, 0.85)$ | $\tau_{TR} = (4.25, 5, 5.75, 0.85)$ | 0.85 |
| $\lambda_{TO} = (0.000018, 0.000022, 0.000025, 0.9)$ | $\tau_{TO} = (6.8, 8, 9.2, 0.9)$ | 0.9 |

## 6.3 Conversion of the Data to Same Degree of Confidence

In **Table 4**, different values of confidence levels ($\omega$) are assigned to each component because they represent the degree of membership or the level of certainty in the fuzzy data associated with that component's failure and repair rates. This variation arises because of various reasons like component specific uncertainty, expert opinions or the accuracy of the data collection process. To maintain data consistency and ensure uniformity across calculations, a uniform confidence level is used. This makes it easier to interpret and compare reliability indices.

To maintain the flatness of the data, generalizing it is essential after fuzzifying it. Generalization helps to convert all the fuzzy values up to same satisfaction level. This process is given as,

$\omega_{min} = \min(0.8,0.85,0.9,0.8,0.8,0.85,0.85,0.85,0.85,0.8,0.85.0.9) = 0.80$.

**Table 5** shows the generalize values for each parameter. The data in the following **Table 5** has been modified to maintain its flatness. With a same degree of confidence, all the parameters are transformed. Now, arithmetic operations can be applied to these failure and repair rates to perform various analysis.

**Table 5.** Values of the component parameters with the same degree of confidence.

| Failure rate($\lambda$) (in hrs.) | Repair time ($\tau$) (in hrs.) | Weightage $\omega min$ |
|---|---|---|
| $\lambda^*_{BL} = (0.000144, 0.000169, 0.000194, 0.000194, 0.8)$ | $\tau^*_{BL} = (6.80, 8, 9.20, 9.20, 0.8)$ | 0.80 |
| $\lambda^*_{PS} = (0.000008, 0.000009, 0.000011, 0.000011, 0.85)$ | $\tau^*_{PS} = (4.25, 4.96, 5.04, 5.75, 0.85)$ | 0.80 |
| $\lambda^*_{H} = (0.000018, 0.000021, 0.000024, 0.000024, 0.9)$ | $\tau^*_{H} = (3.4, 3.93, 4.70, 4.60, 0.9)$ | 0.80 |
| $\lambda^*_{GB} = (0.000007, 0.000008, 0.000009, 0.000009, 0.8)$ | $\tau^*_{GB} = (5.10, 6, 6, 6.90, 0.8)$ | 0.80 |
| $\lambda^*_{G} = (0.000005, 0.000006, 0.000007, 0.000007, 0.8)$ | $\tau^*_{G} = (6.80, 8, 8, 9.20, 0.8)$ | 0.80 |
| $\lambda^*_{BR} = (0.000004, 0.000005, 0.000005, 0.000005, 0.85)$ | $\tau^*_{BR} = (1.70, 1.98, 2.02, 2.30, 0.85)$ | 0.80 |
| $\lambda^*_{GE} = (0.000008, 0.000009, 0.000011, 0.000011, 0.85)$ | $\tau^*_{GE} = (3.4, 3.96, 4.04, 4.60, 0.85)$ | 0.80 |
| $\lambda^*_{CS} = (0.000023, 0.000027, 0.000032, 0.000032, 0.85)$ | $\tau^*_{CS} = (3.4, 3.96, 4.04, 4.60, 0.85)$ | 0.80 |
| $\lambda^*_{YD} = (0.000002, 0.000002, 0.000003, 0.000003, 0.85)$ | $\tau^*_{YD} = (3.4, 3.96, 4.04, 4.60, 0.85)$ | 0.80 |
| $\lambda^*_{YM} = (0.000003, 0.000003, 0.000004, 0.000004, 0.8)$ | $\tau^*_{YM} = (4.25, 5, 5, 5.75, 0.8)$ | 0.80 |
| $\lambda^*_{TR} = (0.000002, 0.000002, 0.000003, 0.000003, 0.85)$ | $\tau^*_{TR} = (4.25, 4.96, 5.04, 5.75, 0.85)$ | 0.80 |
| $\lambda^*_{TO} = (0.000018, 0.000022, 0.000025, 0.000025, 0.9)$ | $\tau^*_{TO} = (6.8, 7.87, 8.13, 9.20, 0.9)$ | 0.80 |

## 7. Solution Methodology

Knezevic and Odoom (2001) applied AND-OR logic gates to define the failure rate and repair time expressions, as shown in **Table 6**.

**Table 6.** Basic expression of the Lambda-Tau methodology.

| Logic gate | AND | | OR | |
|---|---|---|---|---|
| | $\lambda_{AND}$ | $\tau_{AND}$ | $\lambda_{OR}$ | $\tau_{OR}$ |
| **Expressions** | $\prod_{j=1}^{n}\lambda_j\left[\sum_{i=1}^{n}\prod_{j=1,i\neq j}^{n}\tau_j\right]$ | $\frac{\prod_{i=1}^{n}\tau_i}{\sum_{j=1}^{n}\prod_{i=1,}^{n}\tau_i}$ | $\sum_{i=1}^{n}\lambda_i$ | $\frac{(\sum_{i=1}^{n}\lambda_i\tau_i)}{\sum_{i=1}^{n}\lambda_i}$ |

Built on the above expressions, the failure rate and repair time of the Wind Turbine are defined as shown in the following equations.

$$\lambda_{WT} = \lambda_{BL} + \lambda_{PS} + \lambda_H + \lambda_{BE} + \lambda_G + \lambda_{BR} + \lambda_{GE} + \lambda_{CS} + \lambda_{YD} + \lambda_{YM} + \lambda_{TR} + \lambda_{TO} \tag{4}$$

$$\tau_{WT} = \frac{\begin{pmatrix}\lambda_{BL}\tau_{BL}+\lambda_{PS}\tau_{PS}+\lambda_H\tau_H+\lambda_{BE}\tau_{BE}+\lambda_G\tau_G+\lambda_{BR}\tau_{BR}+\\ \lambda_{GE}\tau_{GE}+\lambda_{CS}\tau_{CS}+\lambda_{YD}\tau_{YD}+\lambda_{YM}\tau_{YM}+\lambda_{TR}\tau+\lambda_{TO}\tau_{TO}\end{pmatrix}}{\lambda_{WT}} \tag{5}$$

By applying the arithmetic operations described in Sections 5.3.3 and 5.3.4, and using the data presented in **Table 5** with Equations (4) and (5), the resulting values are obtained and presented in **Table 7** below.

**Table 7.** Fuzzy values of the failure rate and repair time of the wind turbine.

| Parameter | Fuzzy Value |
|---|---|
| Failure rate of wind turbine ($\lambda_{WT}$) | (0.000241, 0.000282,0.000326, 0.000326) |
| Repair time of wind turbine ($\tau_{WT}$) | (4.300490,5.913704,7.931495,10.650124) |

## 8. Results and Discussion

### 8.1 Reliability Analysis of Wind Turbine System

In this section, author discusses the performance of the wind turbine plant. Using the data presented in **Table 7**, various reliability metrics, such as Mean Time to Failure (MTTF), Mean Time to Repair (MTTR), Mean Time Between Failures (MTBF), reliability, maintainability, availability, and the Expected Number of Failures (ENOF), are calculated using the expressions provided in **Table 8** for the wind turbine. **Table 9** shows the numerical values for these reliability metrics. Each reliability parameter is calculated with 80% confidence level. These values are expressed as generalized trapezoidal fuzzy numbers, with a confidence level of 0.80 and a tolerance of 15%. **Table 8** presents the expressions for reliability indices as proposed by Tanaka et al. (1983).

**Table 8.** Expression for reliability indices.

| Parameter | Expression |
|---|---|
| MTTF | $\mathrm{MTTF}_{WT} = \frac{1}{\lambda_{WT}}$ |
| MTTR | $\mathrm{MTTR}_{WT} = \frac{1}{\mu_{WT}} = \tau_{WT}$ |
| MTBF | $\mathrm{MTBF}_{WT} = \frac{1}{\lambda_{WT}} + \tau_{WT}$ |
| Reliability | $R_{WT} = e^{-\lambda_{WT}\,t}$ |
| Unreliability | $U_{WT} = 1 - e^{-\lambda_{WT}\,t}$ |
| Maintainability | $M_{WT} = 1 - e^{-\mu_{WT}\,t}$ |
| Availability | $A_{WT} = \frac{\mu_{WT}}{(\mu_{WT}+\lambda_{WT})} + \frac{\lambda_{WT}}{(\mu_{WT}+\lambda_{WT})}e^{-(\mu_{WT}+\lambda_{WT})t}$ |
| ENOF (expected number of failure) | $\frac{\mu_{WT}\lambda_{WT}\,t}{(\mu_{WT}+\lambda_{WT})} + \frac{\lambda_{WT}{}^2}{(\mu_{WT}+\lambda_{WT})^2}\left[1 - e^{-(\mu_{WT}+\lambda_{WT})t}\right]$ |

**Table 9.** Reliability indices fuzzified and defuzzified values.

| Parameter | Fuzzified values | Defuzzied values |
|---|---|---|
| MTTF | (3065.3486, 3065.3486, 3540.4668, 4147.2364) | 3454.6001 |
| MTTR | (4.3005, 5.9137, 7.9315, 10.6501) | 7.1990 |
| MTBF | (3069.6491, 3071.2623, 3548.3983, 4157.8865) | 3461.7991 |
| Reliability | (0.999674, 0.999674, 0.999718, 0.999759) | 0.9997 |
| Unreliability | (0.000241, 0.000282, 0.000326, 0.000326) | 0.0003 |
| Maintainability | (0.0896 ,0.1185, 0.1556, 0.2075) | 0.1428 |
| Availability | (0.9997, 0.9997, 0.9997, 0.9998) | 0.9997 |
| ENOF (expected number of failure) | (0.0002, 0.0002, 0.0002, 0.0003) | 0.0003 |

The system's reliability is extremely high, with a defuzzied value of 0.9997, while unreliability is minimal at 0.0003. The maintainability is moderate at 14.28%, implying that repairs are achievable but not instantaneous. The availability is almost perfect at 99.97%, meaning the system remains operational most of the time. Lastly, the expected number of failures (ENOF) is very low at 0.0003, indicating a negligible chance of failure over time. Overall, the system is highly reliable, maintainable, and available for continuous operation.

Using the data presented in **Table 5** and Equation (1), the Failure rate, Repair time, MTTF, MTTR, MTBF, Reliability, Maintainability, availability, and ENOF for alpha cuts from 0 to 0.8 are calculated and listed in **Table 10**, **Table 11**, and **Table 12** respectively.

The fuzzy values of the parameters Failure rate (**Figure 6**), Repair time (**Figure 7**), MTTF (**Figure 8**), MTTR (**Figure 9**), MTBF (**Figure 10**), Reliability (**Figure 11**), Maintainability (**Figure 12**), Availability (**Figure 13**), and ENOF (**Figure 14**) are represented as GTFNs up to maximum confidence level 0.80. **Figures 8** to **13** represent the performance measures of the wind turbine plant corresponding to membership degrees varying from 0 to 0.8. From the **Figures 8** to **13**, it is observed that for each parameter, as the membership degree increases from 0 to 0.8, the left cut (least value) increases, and the right cut (greatest value) decreases.

**Table 10.** Alpha cut range of failure rate, repair time and MTTF.

| Degree of membership ($\alpha$) | Failure rate (per hours) | | Repair time (per hours) | | MTTF | |
|---|---|---|---|---|---|---|
| | Least | Greatest | Least | Greatest | Least | Greatest |
| 0 | 0.000241124 | 0.000326227 | 4.300489896 | 10.65012428 | 3065.348613 | 4147.236359 |
| 0.05 | 0.000243707 | 0.000326227 | 4.401315757 | 10.48020996 | 3065.348613 | 4109.313262 |
| 0.1 | 0.00024629 | 0.000326227 | 4.502141617 | 10.31029564 | 3065.348613 | 4071.390165 |
| 0.15 | 0.000248873 | 0.000326227 | 4.602967478 | 10.14038132 | 3065.348613 | 4033.467068 |
| 0.2 | 0.000251455 | 0.000326227 | 4.703793339 | 9.970467002 | 3065.348613 | 3995.543972 |
| 0.25 | 0.000254038 | 0.000326227 | 4.804619200 | 9.800552684 | 3065.348613 | 3957.620875 |
| 0.3 | 0.000256621 | 0.000326227 | 4.905445061 | 9.630638366 | 3065.348613 | 3919.697778 |
| 0.35 | 0.000259204 | 0.000326227 | 5.006270921 | 9.460724048 | 3065.348613 | 3881.774681 |
| 0.4 | 0.000261787 | 0.000326227 | 5.107096782 | 9.29080973 | 3065.348613 | 3843.851584 |
| 0.45 | 0.000264369 | 0.000326227 | 5.207922643 | 9.120895412 | 3065.348613 | 3805.928487 |
| 0.5 | 0.000266952 | 0.000326227 | 5.308748504 | 8.950981094 | 3065.348613 | 3768.00539 |
| 0.55 | 0.000269535 | 0.000326227 | 5.409574365 | 8.781066775 | 3065.348613 | 3730.082293 |
| 0.6 | 0.000272118 | 0.000326227 | 5.510400225 | 8.611152457 | 3065.348613 | 3692.159196 |
| 0.75 | 0.000279866 | 0.000326227 | 5.812877808 | 8.101409503 | 3065.348613 | 3578.389905 |
| 0.8 | 0.000282449 | 0.000326227 | 5.913703669 | 7.931495185 | 3065.348613 | 3540.466808 |

**Table 11.** Alpha cut range of MTTR, MTBF and reliability.

| Degree of membership ($\alpha$) | MTTR | | MTBF | | Reliability | |
|---|---|---|---|---|---|---|
| | Least | Greatest | Least | Greatest | Least | Greatest |
| 0 | 4.300489896 | 10.65012428 | 3069.649103 | 4157.886484 | 0.999673826 | 0.999758905 |
| 0.05 | 4.401315757 | 10.48020996 | 3069.749929 | 4119.793472 | 0.999673826 | 0.999756323 |
| 0.1 | 4.502141617 | 10.31029564 | 3069.850755 | 4081.700461 | 0.999673826 | 0.99975374 |
| 0.15 | 4.602967478 | 10.14038132 | 3069.951581 | 4043.60745 | 0.999673826 | 0.999751158 |
| 0.2 | 4.703793339 | 9.970467002 | 3070.052407 | 4005.514439 | 0.999673826 | 0.999748576 |
| 0.25 | 4.8046192 | 9.800552684 | 3070.153233 | 3967.421427 | 0.999673826 | 0.999745994 |
| 0.3 | 4.905445061 | 9.630638366 | 3070.254058 | 3929.328416 | 0.999673826 | 0.999743412 |
| 0.35 | 5.006270921 | 9.460724048 | 3070.354884 | 3891.235405 | 0.999673826 | 0.99974083 |
| 0.4 | 5.107096782 | 9.29080973 | 3070.45571 | 3853.142393 | 0.999673826 | 0.999738248 |
| 0.45 | 5.207922643 | 9.120895412 | 3070.556536 | 3815.049382 | 0.999673826 | 0.999735666 |
| 0.5 | 5.308748504 | 8.950981094 | 3070.657362 | 3776.956371 | 0.999673826 | 0.999733084 |
| 0.55 | 5.409574365 | 8.781066775 | 3070.758188 | 3738.86336 | 0.999673826 | 0.999730502 |
| 0.6 | 5.510400225 | 8.611152457 | 3070.859014 | 3700.770348 | 0.999673826 | 0.99972792 |
| 0.75 | 5.812877808 | 8.101409503 | 3071.161491 | 3586.491315 | 0.999673826 | 0.999720173 |
| 0.8 | 5.913703669 | 7.931495185 | 3071.262317 | 3548.398303 | 0.999673826 | 0.999717591 |

**Table 12.** Alpha cut range of maintainability, availability and ENOF.

| Degree of membership ($\alpha$) | Maintainability | | Availability | | ENOF | |
|---|---|---|---|---|---|---|
| | Least | Greatest | Least | Greatest | Least | Greatest |
| 0 | 0.089622216 | 0.207475332 | 0.999708971 | 0.999769877 | 0.000241097 | 0.000326176 |
| 0.05 | 0.091424287 | 0.20423153 | 0.999708405 | 0.999767676 | 0.00024368 | 0.000326176 |
| 0.1 | 0.093226358 | 0.200987729 | 0.999707838 | 0.999765476 | 0.000246262 | 0.000326176 |
| 0.15 | 0.095028429 | 0.197743927 | 0.999707272 | 0.999763275 | 0.000248844 | 0.000326176 |
| 0.2 | 0.096830501 | 0.194500125 | 0.999706706 | 0.999761075 | 0.000251426 | 0.000326176 |
| 0.25 | 0.098632572 | 0.191256323 | 0.99970614 | 0.999758874 | 0.000254008 | 0.000326176 |
| 0.3 | 0.100434643 | 0.188012521 | 0.999705574 | 0.999756674 | 0.00025659 | 0.000326176 |
| 0.35 | 0.102236714 | 0.184768719 | 0.999705007 | 0.999754473 | 0.000259172 | 0.000326176 |
| 0.4 | 0.104038786 | 0.181524917 | 0.999704441 | 0.999752273 | 0.000261754 | 0.000326176 |
| 0.45 | 0.105840857 | 0.178281115 | 0.999703875 | 0.999750072 | 0.000264336 | 0.000326176 |
| 0.5 | 0.107642928 | 0.175037314 | 0.999703309 | 0.999747872 | 0.000266918 | 0.000326176 |
| 0.55 | 0.109445000 | 0.171793512 | 0.999702743 | 0.999745671 | 0.000269500 | 0.000326176 |
| 0.6 | 0.111247071 | 0.16854971 | 0.999702176 | 0.99974347 | 0.000272083 | 0.000326176 |
| 0.75 | 0.116653285 | 0.158818304 | 0.999700478 | 0.999736869 | 0.000279829 | 0.000326176 |
| 0.8 | 0.118455356 | 0.155574502 | 0.999699912 | 0.999734668 | 0.000282411 | 0.000326176 |

In **Tables 10**, **11**, and **12**, the various Reliability indices are given at different satisfaction levels. The MTTF lies within the interval (3065.3486, 3540.4668) with a confidence level of 0.8. Below this confidence level, the lower value of each alpha cut remains constant, while the upper value increases, as shown in **Figure 5**. A similar pattern is observed for the other parameters. The MTTR lies within the interval (5.9137, 7.9315) with a confidence level of 0.8, as displayed in **Figure 9**. The MTBF falls within the interval (3071.2623, 3548.3983) at a 0.8 confidence level, where, below this level, the lower value approximately remains fixed and the upper value increases, as shown in **Figure 10**. The reliability lies within the interval (0.999673, 0.999717) at a confidence level of 0.8 as shown in **Figure 11**. Maintainability is in the interval (0.118455, 0.155574), with a confidence level of 0.8 as shown in **Figure 12**, while availability falls within (0.999670, 0.999735), with a confidence level of 0.8 as shown in **Figure 13**. The ENOF lies in the interval (0.000282, 0.000326) with a confidence level of 0.8, where, below this level, the upper value of each alpha cut remains fixed while the lower value increases, as illustrated in **Figure 14**. Overall, the system remains highly reliable, with only slight variations in the reliability and availability as confidence level changes.

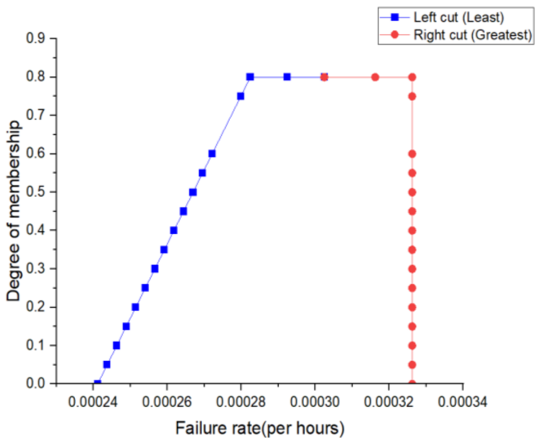


**Figure 6.** Failure rate of wind turbine.

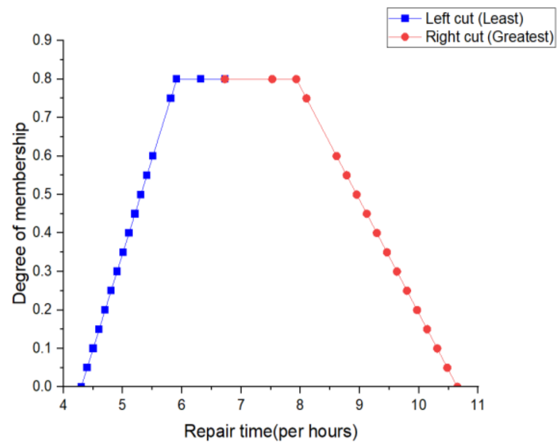


**Figure 7.** Repair time of wind turbine.

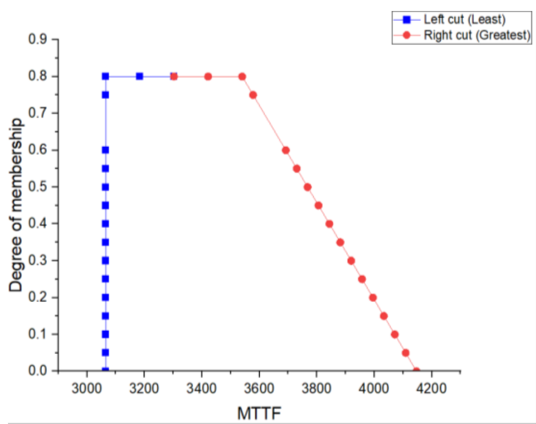


**Figure 8.** MTTF of wind turbine.

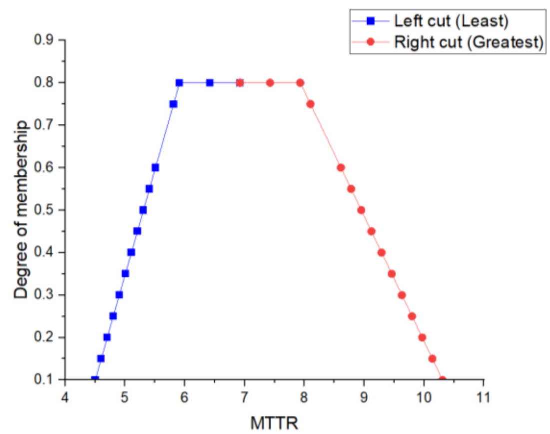


**Figure 9.** MTTR of wind turbine.

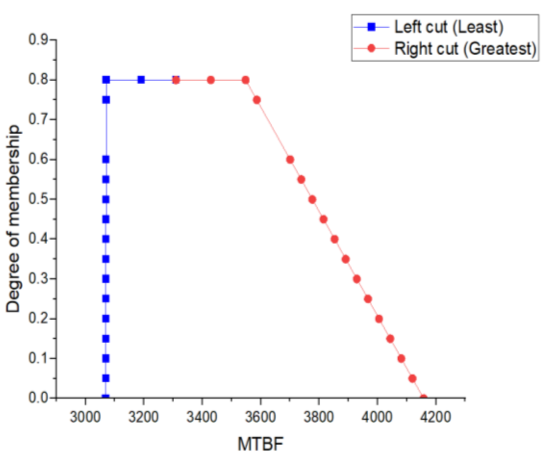


**Figure 10.** MTBF of wind turbine.

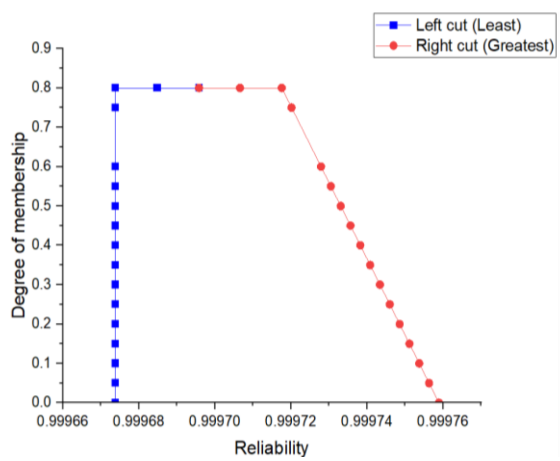


**Figure 11.** Reliability of wind turbine.

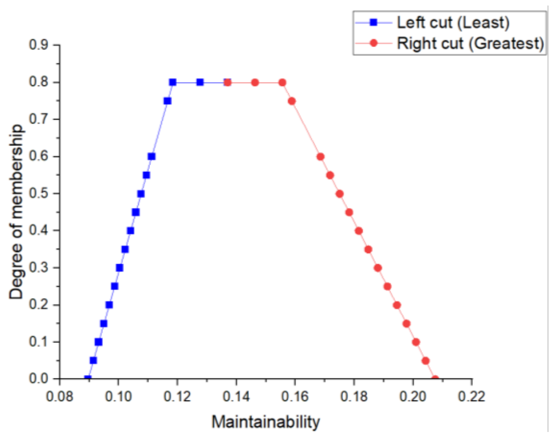


**Figure 12.** Maintainability of wind turbine.

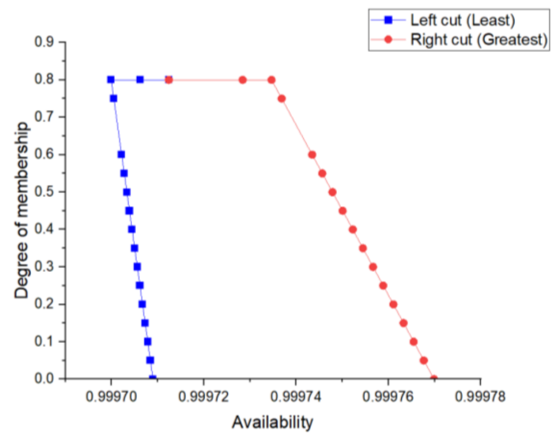


**Figure 13.** Availability of wind turbine.

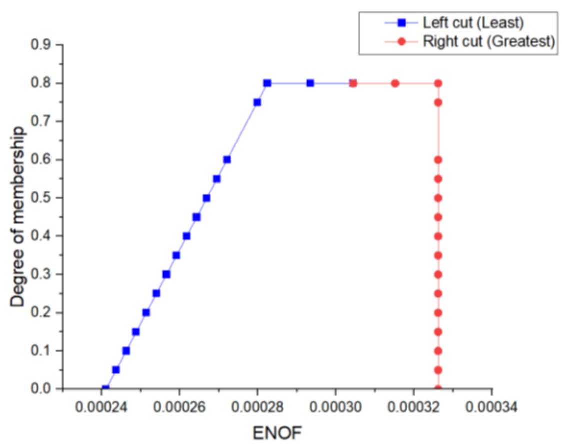


**Figure 14.** ENOF of wind turbine.

## 8.2 Ranking of the Component of the Wind Turbine System

After various reliability parameters have been determined, the authors proceed on to determine the ranking using section 5.5. The component rankings are shown in the following **Table 13**.

**Table 13.** Ranking to identify the wind turbine system's critical component.

| Components | $V(\lambda_{WT}, \lambda_{Component,})$ | $R(\lambda_{WT}, \lambda_{Component})$ | Rankings |
|---|---|---|---|
| Blade | (0.000098,0.000113,0.000132,0.000132) | 0.000474886 | 10 |
| Pitch system | (0.000233,0.000273,0.000316,0.000316) | 0.001138208 | 6 |
| Hub | (0.000223,0.000262,0.000302,0.000302) | 0.001088737 | 7 |
| Gearbox: Bearing | (0.000234,0.000274,0.000317,0.000317) | 0.001142865 | 5 |
| Gearbox: Gear | (0.000236,0.000277,0.000320,0.000320) | 0.00115234 | 4 |
| Brake | (0.000237,0.000278,0.000321,0.000321) | 0.001157118 | 3 |
| Generator | (0.000233,0.000273,0.000316,0.000316) | 0.001138208 | 6 |
| Control system | (0.000218,0.000255,0.000295,0.000295) | 0.001062571 | 9 |
| Yaw system: Yaw driver | (0.000239,0.000280,0.000324,0.000324) | 0.001166573 | 1 |
| Yaw system: Yaw motor | (0.000238,0.000279,0.000322,0.000322) | 0.001161845 | 2 |
| Transformer | (0.000239,0.000280,0.000324.0.000324) | 0.001166573 | 1 |
| Tower | (0.000223,0.000223,0.000301,0.000301) | 0.001086377 | 8 |

According to the **Table 13**, the component Blade has the lowest rank of 10, whereas the subcomponent Yaw Driver of the component Yaw system and the component Transformer have the greatest rank of 1. It suggests that the Subcomponent Yaw Driver from the Yaw system and the Transformer are the two most significant parts of the systems, with the Blade as the least essential. Based on the component ranking, experts can plan and prioritize their maintenance strategy. It is best to take care of the most important parts of the system first, like the transformer and yaw driver, to reduce the probability of system failures.

The advantages of using GTFNs over traditional methods. GTFNs help to represent uncertainty more accurately, making the reliability results closer to real conditions. They also support better decision-making by considering different confidence levels, which improves maintenance planning. Unlike traditional methods, our approach includes both routine and preventive maintenance, helping to reduce system downtime. In addition, our method ranks the components based on their reliability impact, making it easier for maintenance teams to focus on the most important parts.

## 9. Conclusions

Proposed study focused on the investigation of a wind turbine system by incorporating the concept of fuzzy reliability through generalized trapezoidal fuzzy numbers (GTFNs). Using the available data and assuming that preventative and routine maintenance are carried out, the authors obtained the different performance measures of wind turbine plant. Analysis has been done on reliability parameters such as MTTF, MTTR, MTBF, reliability, availability, maintainability, and ENOF. In order to describe the data in a fuzzy environment, the authors also provide a generalized trapezoidal membership function, which is helpful in addressing the uncertainty problem. With a 0.80 confidence level and a 15% bilateral tolerance, all the parameters are summarized and depicted with the help of graphs.

The different reliability indices have been calculated (refer **Tables 9**, **10**, **11**, and **12** and corresponding **Figures 6** to **14**). The rankings of the different wind turbine plant components are shown in the **Table 13**. The higher-ranked component is the most important, while a lower-ranked component is the least important. The highest ranked component in the total framework scheme needs more attention than the other components. The obtained result shows that the highest rank components are **Yaw Driver and Transformer**, while the **Blade is the least rank component of** wind turbine. The ranking of the components play crucial role in overall performance of a system and the maintenance team must plan maintenance strategy as per components ranking to optimize the perform of the system. Also, to prevent a system from breakdown redundancy can be used for the sensitive components. This leads to lower repair costs and less downtime, which improves the overall performance and profit of the wind turbine plant.

From a commercial point of view, this method can be useful for wind farm operators and manufacturers to improve system design and maintenance. It also supports better planning and investment decisions in wind energy projects.

Compared to earlier studies that used crisp values or basic fuzzy methods, our method offers a more flexible and realistic way to assess system performance. Our findings show an improvement over earlier reliability analyses of WTP, as the GTFN-based modelling provides enhanced sensitivity to data variability and better supports decision-making under uncertainty.

This study uses Generalized Trapezoidal Fuzzy Numbers (GTFNs) to assess the reliability of a wind turbine plant. While the method handles uncertainty well, it has a few limitations. The fuzzy parameters are based on expert opinion, which may cause some subjectivity. Also, when the system becomes larger, the calculations can get more complicated. Another limitation is that the study focuses only on static reliability and does not consider changes that happen over time.

This work can be extended in the future by applying the same approach to other type of renewable energy systems like geothermal power plants, nuclear power plants. It can also be used with real-time data to improve accuracy. In this paper, we have used GTFNs for fuzzification. In future work, we plan to explore more complex fuzzy environments like intuitionistic fuzzy or Neuromorphic fuzzy or picture fuzzy environment to further improve the study.

### Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### AI Disclosure

The author(s) declare that no assistance is taken from generative AI to write this article.

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