A Hybrid DES-Python Framework for Wind Turbine Reliability Using Residual Time-Based Failure Modeling

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Abstract. This paper proposes a hybrid modeling framework for wind turbine reliability that integrates Discrete-Event Simulation (DES) in Simio with Python-based statistical validation. The approach employs a residual time algorithm to capture the interaction of concurrent failure modes: electrical, control, and gearbox, while preserving system memory and avoiding artificial resets. Failure and repair processes are characterized by using statistically validated probability distributions. Results from a five-year simulation demonstrate that failures have limited impact on availability due to short repair times. The proposed framework enables realistic turbine simulation and supports availability assessment for designing future availability-based contracts.

Keywords: Discrete-Event Simulation, Python Statistical Validation, Simio Software

Un Marco Híbrido DES-Python para la Confiabilidad de Turbinas Eólicas Mediante el Modelado de Fallas Basado en Tiempo Residual

Resumen. Este trabajo propone un marco híbrido de modelado para la confiabilidad de aerogeneradores que integra Simulación de Eventos Discretos (DES) en Simio con validación estadística basada en Python. El enfoque emplea un algoritmo de tiempo residual para capturar la interacción de modos de falla concurrentes: eléctricos, de control y de la multiplicadora, preservando la memoria del sistema y evitando reinicios artificiales. Los procesos de falla y reparación se caracterizan mediante distribuciones de probabilidad validadas estadísticamente. Los resultados de una simulación de cinco años demuestran que las fallas tienen un impacto limitado en la disponibilidad debido a sus cortos tiempos de reparación. El marco propuesto permite simular el comportamiento de la turbina y evaluar su disponibilidad, apoyando el diseño de contratos futuros basados en disponibilidad.

Palabras clave: Simulación de Eventos Discretos, Validación Estadística con Python, Simio.

Nomenclature

Symbol	Description	Units	Definitions
t	Continuous simulation time	hours	Global system time
k	Event iteration index	-	Discrete event counter
$t_{\{i\}}^{\{(k)\}}$	Residual time to failure of mode i at iteration k	hours	General form
$t_{\{elec\}}^{\{(k)\}}$	Residual time to electrical failure	hours	Electrical subsystem
$t_{\{gear\}}^{\{(k)\}}$	Residual time to gearbox failure	hours	Mechanical subsystem
$t_{\{ctrl\}}^{\{(k)\}}$	Residual time to control failure	hours	Control subsystem
$t_{\{min\}}^{\{(k)\}}$	Time to next failure event	hours	Minimum of all residual times
j	Index of triggering failure mode	-	j ∈ {elec, gear, ctrl}
$S(t)$	System state at time t	-	Operational or Failed
λ_i	Failure rate of mode i	1/hours	Parameter of exponential distribution
TTR_j	Time to repair for failure mode j	hours	Random variable
a_j	*Minimum repair time*	*hours*	*Triangular distribution parameter*
b_j	*Most likely repair time*	*hours*	*Triangular distribution parameter*
c_j	*Maximum repair time*	*hours*	*Triangular distribution parameter*
$t_j^{\{(k+1)\}}$	*Resampled residual time for triggering failure*	*hours*	*Reset after failure*
$t_i^{\{(k+1)\}}$	*Residual time for non-triggering modes*	*hours*	*Remains unchanged*

1 Introduction

The development of wind power has placed wind energy as a vital element for a low-carbon power mix. However, the integration of wind power into contemporary power systems poses many challenges concerning power system reliability, stability, and security. Wind power is characterized as a stochastic power source, while wind turbines are characterized as complex electromechanical systems. Consequently, wind power poses many operational uncertainties (Le Xie et al., 2011).

In this field, wind turbines are prone to various failure modes for both mechanical and electrical systems. Previous studies have indicated that wind turbines are prone to more frequent electrical and control system failures. However, mechanical failures, especially those concerning gearbox failures, are characterized as more costly in terms of wind turbine downtime. Consequently, wind turbine performance is greatly affected not only by the frequency of wind turbine failures but also their duration (Pinar Pérez et al., 2013).

Besides wind turbine failures, wind farms are highly affected by grid-induced disturbances. Such disturbances include voltage dips, short circuits, and changes in grid frequency. These disturbances may induce disconnection or partial disconnection of wind farms. The ability of wind turbines to remain connected during grid-induced disturbances is commonly referred to as Fault Ride Through (FRT). However, wind turbine FRT capability is still insufficiently explored concerning wind turbine reliability and grid-induced disconnections (Saeed et al., 2022).

Traditional methods of analysis in reliability assessment tend to be based on simplistic presumptions that overlook the stochastic nature of interactions between failure modes and external disturbances. In this respect, the application of discrete-event simulation stands out as an efficient approach in the analysis of the evolution of systems over time in the presence of stochastic disturbances (Chiacchio et al., 2020).

In this regard, this paper proposes the application of a discrete-event simulation approach for analyzing wind farm reliability using Simio (Houck & Whitehead, 2019). The methodology considers multiple wind turbine failure modes as well as the effects of grid disturbances. In addition, a hybrid modeling framework is introduced, incorporating Python-based routines for the identification and validation of statistical fits between empirical data and probabilistic distributions (Monterrosa & Pinilla, 2025).. This integration enables a more rigorous estimation of time-to-failure and time-to-repair parameters, improving the robustness and realism of the simulation model. The proposed approach allows for the evaluation of key performance indicators such as turbine availability and energy not supplied, providing valuable insights for supporting decision-making in the design of future availability-based contracts, which are critical in the power sector due to the potentially significant financial penalties associated with non-compliance(Lutz et al., 2020).

While classical approaches such as Monte Carlo simulation, and semi-Markov models provide valuable tools for repairable system reliability analysis, each presents limitations when applied to systems with heterogeneous failure distributions and competing concurrent processes (Elsayed, 2023; Dimitrakopoulou et al., 2025). Specialized tools like ReliaSoft BlockSim or GRIF reduce modeling effort but offer limited flexibility for custom process logic. The hybrid DES-Python framework proposed here addresses these gaps by combining the process-oriented capabilities of Simio with rigorous statistical validation, enabling explicit control over competing failure clocks and repair sequencing without sacrificing distributional flexibility.

The paper is organized as follows: Section 2 presents the methodology and simulation model, Section 3 the results, Section 4 the discussion, and Section 5 the conclusions and future work.

2. Methodology

This approach applies to Discrete-Event Simulation (DES) and a process-oriented approach to examine the reliability of wind turbines. In this case, essential parameters, including simulation clock, interruptions, and the recovery procedure can be used to accurately evaluate availability and energy not supplied.

In accordance with this approach, each turbine will be considered an independent system with three possible subsystem failures, whose random times depend on the

corresponding stochastic distributions (Peng et al., 2023). Based on prior research, the behavior of these elements differs considerably:

Electrical and Control Systems: These elements fail frequently yet require short repair times. In such scenarios, an exponential distribution should be applied (Spinato et al., 2009) . Since it describes a scenario of constant hazard rate (Elsayed, 2023) it can be regarded as an appropriate choice; however, lognormal distribution might be considered in cases of variability of monitoring devices (Shuangwen Sheng, 2013). Gearbox: Being designated as a crucial element, gearboxes fail rarely, however, their impact on system downtimes is significantly high (Faulstich et al., 2011). Due to wear and aging effects, it is better to apply Weibull distributions for this category because they describe an increased hazard rate (Elsayed, 2023).

Data analysis based on the ReliaWind project database (Kandukuri et al., 2016) provides additional confirmation of this hypothesis due to the high-failure/low-downtime pattern of electrical and low-frequency/high-impact drivetrain subsystems.

It should be noted that the model focuses on a single wind turbine, as it represents the fundamental operational unit of a wind farm. This choice enables a detailed and controlled analysis of failure interactions and reliability dynamics, avoiding additional complexities associated with system-level aggregation. Furthermore, this turbine-level formulation provides a modular and scalable basis that can be extended in future work to multi-turbine configurations and full wind farm analysis.

2.1 Statistical Characterization of Failure Data

Prior to developing the discrete-event simulation model, the statistical analysis of the failure data history should be performed to select suitable probability distributions describing time-to-failure processes. It is important since the stochastic inputs of the simulation model should reflect the real behavior of the system properly. The above task is realized through a Python-based framework working with the empirical data represented as spreadsheet files containing information about failure time values. Importing and preprocessing operations include removing empty cells in order to ensure correct statistical results. As a general goal, the analysis aims at checking the goodness-of-fit for the empirical data and a number of candidate probability distributions that can describe different failure behaviors.

A total of six distributions will be considered, namely Normal, Exponential, Poisson, Triangular, Weibull, and Uniform. While the Normal distribution describes symmetric degradation processes typical for the wear-out failure modes, the Exponential distribution implies random failures and can be interpreted as electrical component failure behavior with the constant hazard rate. The Poisson distribution, despite being discrete, can be useful in assessing the number of events taking place within certain time periods, while the Uniform distribution corresponds to equal risk of failures during a bounded period.

In turn, the parameters of the chosen distributions should be defined, which can be done either explicitly (for Normal) or according to engineering interpretations (Mean time between failures – for Exponential). For Poisson distribution, data discretization is performed. Besides, the Weibull distribution is widely used in reliability analysis due

to its flexibility in modeling different failure behaviors, as its shape parameter allows representing both early-life failures and aging-related wear-out mechanisms.

To check the goodness-of-fit (GoF) for the candidates above, the following methods are used:

- Kolmogorov-Smirnov Test (K-S). This method compares empirical distribution function of the analyzed data sample and theoretical cumulative distribution function of the probability model (Massey, 1951).
- Anderson-Darling Test (A-D), available only for Normal and Exponential probability distributions (more sensitive to discrepancies in tails) (Su & Su, 2014).
- Chi-squared test (X^2) comparing frequencies found for each bin in histogram (Rolke & Gongora, 2021).

As a result, the goodness-of-fit test is considered adequate when corresponding p-values meet significance criteria.
The above multi-step approach is taken in order to reduce the likelihood of choosing inappropriate distribution due to the imperfection of a single statistical test. Finally, the results of the above analyses provide the basis for defining the stochastic input of our simulation model (probability models of failures). One can expect exponential behavior (exponential distribution) for some failure modes, which is aligned with memoryless property assumption adopted in the discrete-event simulation formulation of the problem discussed in the following sections.

2.2 Process-Based Failure Modeling Algorithm

The system is modeled as a continuous-time stochastic process with piecewise deterministic evolution, governed by the competition between multiple residual failure times (Dimitrakopoulou et al., 2025). In this framework, a failure event is triggered when any specific residual time reaches zero. Between events, all residual times decrease simultaneously at a uniform rate.

When a failure occurs, the system transitions to a repair state for a duration determined by its specific repair distribution. Upon returning to operation, only the residual time of the triggered failure mode is resampled; all other failure processes retain their remaining values. This approach provides the system with memory, avoiding artificial resets and more accurately representing the interactions between competing failure modes. This theoretical formulation is implemented within the simulation through a process-based discrete event structure that dictates the system's temporal evolution.

2.2.1 Step-by-Step Residual Time-Based Failure Simulation Algorithm

The failure mechanisms of the wind turbine are captured by the discrete-event simulation model based on the process-based failure modeling approach, where the competition between different failure mechanisms is addressed by the inclusion of the residual time approach. This approach is based on an iterative algorithm consisting of

ten steps, which is continuously performed over the entire duration of the simulation period (See Nomenclature section):

Step 1: Initialization of Residual Times - At the beginning of the simulation period, the time to failure for each failure mode is randomly generated based on the probability distribution function of the respective failure mode, as given by

$$\begin{aligned} t_{\{elec\}}^{\{(0)\}} &\sim Exp(\lambda_1) \\ t_{\{gear\}}^{\{(0)\}} &\sim Exp(\lambda_2) \\ t_{\{ctrl\}}^{\{(0)\}} &\sim Exp(\lambda_3) \end{aligned} \quad (1)$$

Step 2: Event Time Determination - At iteration (k), the time at which the next event is expected to occur is calculated by finding the minimum time among the residual times of different failure modes, as given by:

$$t_{\{min\}}^{\{(k)\}} = \backslash min\left(t_{\{elec\}}^{\{(k)\}}, t_{\{gear\}}^{\{(k)\}}, t_{\{ctrl\}}^{\{(k)\}}\right) (2)$$

Step 3: Simulation Time Advancement - The simulation clock is advanced by (t{min}), rrepresenting the time interval between the beginning of the simulation period and the occurrence of the next failure event. This is achieved by incorporating the delay function in the simulation algorithm.

Step 4: Residual Time Update - The residual time for each failure mode is updated by adding the time interval between the beginning of the simulation period and the occurrence of the next failure event, as given by:

$$t^{\{(k+1)\}} = t^{\{(k)\}} + t_{\{min\}}^{\{(k)\}} (3)$$

This step is important because it ensures that the time evolution of the failure mechanisms is consistent.

Step 5: Identification of Triggering Failure - The failure mode that triggers the event is identified as the one whose residual time reaches zero:

$$j = \backslash arg\backslash min_i \left(t_i^{\{(k)\}}\right) \quad (4)$$

Step 6: System Interruption - Having identified the failure mode which triggered the event, the system is changed from the operational state to the failed state corresponding to the identified failure mode. This is done via the interruption mechanism in the simulation model.

$$S(t) = Failed_j \quad (5)$$

Step 7: Repair Process - The system remains in the failed state for a random repair time:

$$TTR_j \sim Triangular(a_j, b_j, c_j) \quad (6)$$

This step involves the repair process which must be undertaken in order for the system to resume normal functioning.

Step 8: System Recovery - Having completed the repair process, the system returns to the operational state. This transition from the failed state to the operational state is explicitly specified in the simulation process.

$$S(t) = Operational \quad (7)$$

Step 9: Selective Reset of Failure Clock - Only the failure clock corresponding to the failure mode which triggered the event has its failure time reset:

$$t_j^{\{(k+1)\}} \sim Exp(\lambda_j) \quad (8)$$

This step reflects the renewal of the failure process which has just occurred.

Step 10: Preservation of Non-Triggering Clocks - The failure times of the failure modes which did not trigger the event remain unchanged following Eq. (9). This step ensures that non-triggering failure processes preserve their temporal progression, avoiding artificial resets and maintaining model realism.

$$t_i^{\{(k+1)\}} = t_i^{\{(k+1)\}}, \backslash quad \forall i \neq j \quad (9)$$

2.2.2 Iterative Execution processes

The above process repeats continuously, forming a simulation cycle that accounts for the competing dynamics between different failure modes and their repair procedures. The advantage of such an approach is that the reliability of the system can be described in more detail than using simple memoryless models. These processes are illustrated in the diagram in **Fig. 1.** In failure management, the process is started by adding one more failure counter, which will keep track of failure occurrences. Then, the minimum time to next failure is evaluated by analyzing each individual failure time from the electrical, gearbox and control subsystems. The process will wait for the calculated minimum time, at which point a failure will be assumed to have occurred. In case of a failure, the turbine state is set to failure mode (value = 3), and the simulation time is recorded at the time of failure. Then the process will analyze the type of failure using a conditional branching statement.

If an electrical failure is detected, the system will find out what the exact electrical failure subtype is. After that, the process introduces a three-time-unit delay, followed by maintenance and repairing operations. When this is done, the next electrical failure will be scheduled by changing the value of the electrical failure time variable.

At this point, the turbine state will be reset to 0, and all the necessary counters and variables will be changed according to the following assignment and delay operations. Similarly, if a failure that is not electrical occurs, the program will check if a gearbox failure happens. In case it does, the system will detect the gearbox failure subtype and schedule another failure using the appropriate gearbox failure time variable. As above, there will be a series of assignments and delay operations.

If neither electrical nor gearbox failure is registered, the last remaining possibility is control system failure. The system will again determine the type of failure in this group and perform some maintenance delay operations. When this is done, it will schedule the next control failure by changing the control failure time variable. Finally, the process will end by changing back all necessary parameters to make sure that the turbine goes back to working condition and resetting the active failure flag.

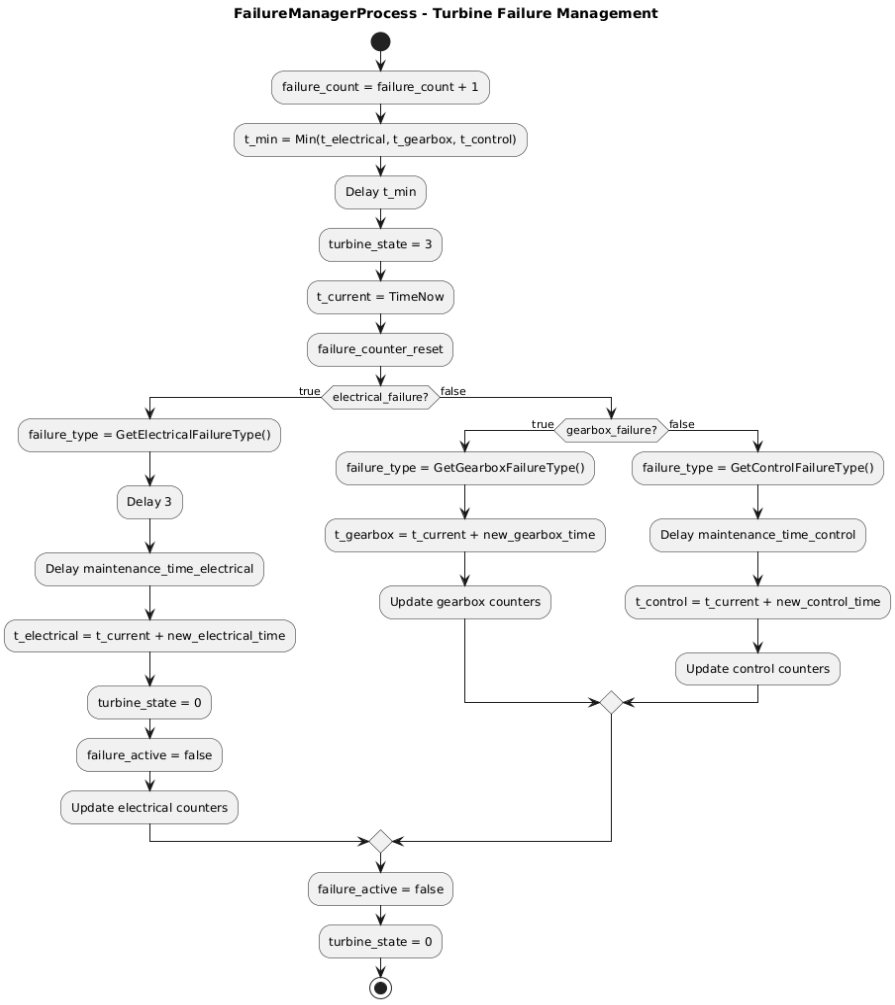

Fig 1. Schematic of discrete failure simulation processes.

3 Case Study: Reliability Analysis of a Wind Turbine

This case study considers a wind turbine system in which multiple failure mechanisms compete over time. The objective is to evaluate system reliability and operational performance using the discrete-event simulation model based on the residual time approach described in the previous section. The system is assumed to be subject to three main failure modes: electrical failures, mechanical (gearbox) failures, and control system failures. Each failure mode is modeled as an independent stochastic process.

The datasets used in this study are publicly available at the following repository (Alvarez, 2026) and were compiled from reliability studies reported in the literature (Shuangwen Sheng, 2013; Spinato et al., 2009) and organized in spreadsheet format to support preprocessing, statistical analysis, and integration into the simulation model.

3.1 Statistical Validation and Characterization of Distributions

The reliability of the wind farm simulation relies on the accurate characterization of stochastic failure events. Statistical analysis and validation were carried out using Google Colab, and Python-based data analysis tools, including Pandas, Matplotlib, Seaborn, and SciPy.

For the electrical system, we analyzed a dataset of time-between-failures (TBF) to verify its alignment with an Exponential distribution, which is the theoretical standard for modeling random, "memoryless" electrical faults. The histogram representing this sample is shown in **Fig. 2**. A visual inspection was conducted through a histogram with a Kernel Density Estimation (KDE) curve, which illustrates the frequency of failure events over time. This visualization confirms a high density of failures at shorter intervals with a progressively thinning "tail," a characteristic behavior of the exponential decay model. The calculated Mean Time Between Failures (MTBF) of 3,000 hours was plotted as a central reference point.

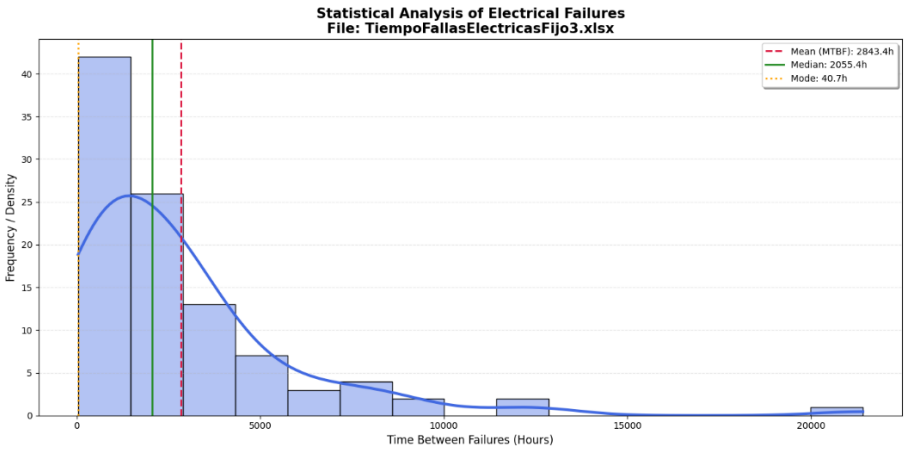

Fig. 2. Histogram of time-between-failures for the electrical system.

To validate this model, three Goodness-of-Fit (GoF) tests were performed. The Kolmogorov-Smirnov (K-S) test yielded a robust p-value of 0.3928, and the Anderson-Darling (A-D) test resulted in a PASS. These results are critical in reliability engineering, as they confirm that the maximum distance between the empirical data and the theoretical model is statistically negligible, even in the distribution's tails where high-impact rare outages occur. Although the Chi-Squared test (X^2) showed a minor deviation (p=0.0119) likely due to sensitivity in data binning, the strong convergence of the continuous tests (K-S and A-D) provides a solid justification for using the Exponential (Mean=3000.0) distribution. This ensures that the subsequent simulation

of turbine availability and energy not supplied (ENS) is grounded in statistically sound parameters.

The reliability of mechanical components, particularly the gearbox, was modeled to capture wear-out characteristics. Unlike electrical systems, drive trains experience progressive fatigue; thus, a Weibull distribution (k=2.5, λ=20,000 hours) was fitted to the Time Between Failures (TBF) dataset. The resulting distribution shows a right-skewed shape typical of components in their wear-out phase (k > 1). Statistical validation was confirmed via Goodness-of-Fit (GoF) tests, where the K-S test (p=0.1365) and A-D test (p=0.1784) both exceeded the 0.05 significance threshold. These results justify using this Weibull model as the primary temporal reference for mechanical failures in the simulation.

The assessment of control systems focused on a constant failure rate model, typical for electronic and software components. A dataset of 99 failure events was analyzed against an Exponential distribution (MTBF of 10,000 hours). The sample exhibited a characteristic exponential decay, with a maximum interval of 53,980.90 hours and a skewness (1.98) consistent with a memoryless process. The model was validated through K-S (p=0.6478) and Chi-Squared (p=0.4899) tests. Exceeding the 0.05 threshold confirms the suitability of the Exponential model for the discrete-event simulation.

Upon failure, the system transitions to a repair state where downtime is modeled using Triangular distributions to account for maintenance uncertainty. A dataset of 99 repair events was fitted to a distribution defined by a minimum (a=5), mode (c=50), and maximum (b=500) hours. This geometry is effective for modeling logistics constrained by physical limits. Statistical validation through K-S (p=0.2358) and other GoF tests (p=0.1045) confirmed that the data follows the Triangular model. These parameters allow for a realistic representation of repair durations and maintenance scheduling within the simulation framework.

3.1 Simulation by using software SIMIO

To demonstrate the proposed reliability modeling technique, a wind turbine case study was developed using Simio, a discrete-event simulation software based on process-oriented and object-oriented modeling. Simio was selected because it allows the implementation of custom failure processes, event scheduling, state management, and concurrent stochastic processes, making it particularly suitable for reliability analysis involving multiple interacting failure modes. The complete model implementation is available in the file *SIMULATIONinSIMIO.spfx* included in the dataset.

For simplicity, the wind turbine is modeled as a single server using a process-based reliability approach that provides full control over failure occurrence and repair mechanisms. Three failure modes are considered: electrical, gearbox, and control system failures. Each mode is represented by an independent stochastic process with its own time-to-failure distribution: exponential (MTTF = 3000 h) for electrical failures, Weibull (shape = 2.5, scale = 20,000 h) for gearbox failures, and exponential (MTTF = 5000 h) for control system failures. Repair durations are modeled using triangular distributions to account for uncertainty in maintenance times.

As mentioned earlier, each failure process consists of six consecutive actions performed at certain points of the simulation run. These actions are Delay, Decide,

Interrupt, Repair, Resume and Loop, and they define the whole process cycle in a straightforward manner. The Delay action refers to time to failure of each process, which occurs stochastically. After this point is accomplished, the Decide action checks whether the turbine was operating before the failure. Thus, this action excludes simultaneous occurrence of several failures within the turbine.

After the turbine state check is passed successfully, the Interrupt action is called, causing failure event occurrence, interrupting turbine operation. The next step in the failure process is described by the Repair action, which models the process of restoring failed equipment. Specifically, the additional delay is set for each turbine component, which is drawn from a specific distribution.

Once repair completion is achieved, the Resume action is executed to switch back to the operational state, and normal operation continues. Finally, the Loop action is performed to repeat the process cycle infinitely until the end of simulation. Therefore, these six actions constitute the whole failure process for each turbine subsystem.

One important characteristic of the model presented here lies in the fact that all processes are independent but executed simultaneously, each having its own internal timer. This leads to automatic failure event competition, in which only one process reaches its failure event point first, determining the failure mode occurring for the turbine. This approach presents a much more realistic model of turbine operation than those relying on the independence of failures or any other assumption of that kind.

The initialization of this failure model consists in turning on all three subprocesses at once. This procedure causes continuous monitoring of turbine failures over the whole simulation time interval. The simulation represented a total operation period of five years, during which 15 electrical failures, 3 mechanical (gearbox) failures, and 5 control system failures were recorded.

Table 1 summarizes the key quantitative reliability indicators derived from the five-year simulation. Over the 43,800-hour simulation horizon, a total of 23 failure events were recorded across all subsystems. The cumulative downtime was estimated using the modal repair time of the triangular distribution (50 hours), yielding approximately 750 hours for electrical failures, 150 hours for gearbox failures, and 250 hours for control system failures, resulting in a total downtime of 1,150 hours. The mean system availability over the simulation period was therefore estimated at 97.4%, computed as the ratio of operational time to total simulation time. It should be noted that the present results correspond to a single simulation run. To obtain statistically robust estimates and associated confidence intervals, a minimum of 30 independent replications is recommended in future work, enabling the computation of mean availability with 95% confidence bounds. These quantitative indicators provide a concrete basis for supporting availability-based contract design, where compliance thresholds and penalty clauses are typically defined around target availability levels.

To complement these results, a video demonstrating the simulation run is included in the dataset (file name "TurbineFailSimulation.mp4"), and a representative capture of this animation can be seen in **Fig. 3**. It should be noted that the time scales in the video have been altered to facilitate a detailed observation of each failure and recovery event.

Table 1. Summary of simulation results over a five-year horizon (43,800 hours).

Subsystem	Failures	Estimated Downtime (h)	Contribution to Unavailability (%)
Electrical	15	750	65.2%
Gearbox	3	150	13.0%
Control	5	250	21.8%
Total	**23**	**1,150**	**100%**
Mean Availability			**97.4%**

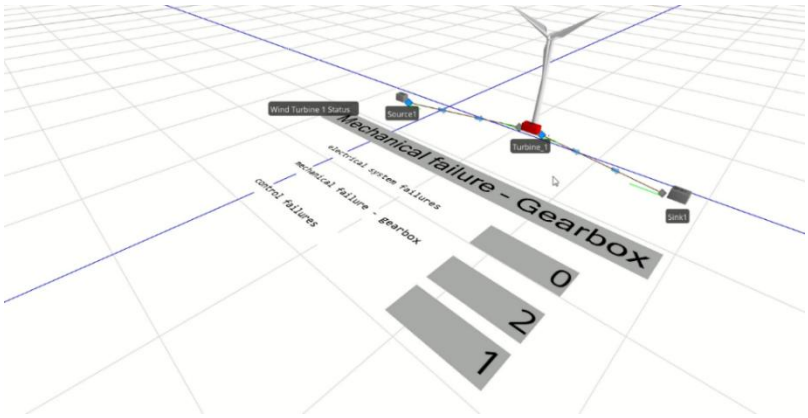

Fig. 3. Snapshot of the animation simulation for event observation in Simio, illustrating the transition from operational to failed state within the discrete-event simulation environment.

4 Discussion of Results

The results validate the hybrid framework's ability to mirror the complex stochastic nature of wind turbines. The competitive residual time approach proved superior to traditional models by accurately reflecting how concurrent failure modes interact without artificial resets.

The simulation clearly distinguishes the operational impact of different subsystems: while electrical and control failures are frequent, their "memoryless" nature and rapid repair times mean they barely affect long-term availability. In contrast, gearbox failures emerge as the critical reliability bottleneck; their alignment with the Weibull distribution (k=2.5) confirms that wear-out and aging are the primary drivers of significant downtime.

Furthermore, the statistical consistency achieved (high p-values in K-S and A-D tests) confirms that the Python-Simio integration effectively eliminates model bias. By grounding repair cycles in triangular distributions, the model successfully incorporates

the logistical uncertainties of maintenance, providing a highly realistic estimation of turbine availability and overall system resilience.
Several limitations should be acknowledged. The model focuses on a single turbine, omitting system-level effects such as shared maintenance resources or correlated failures across a wind farm. Results are based on a single simulation run, which limits statistical robustness; future work should incorporate at least 30 replications to derive confidence intervals. Additionally, the model does not account for external factors such as wind variability or grid disturbances, and repair distributions were derived from literature rather than site-specific data. Addressing these aspects in future extensions will strengthen the framework's applicability to full wind farm reliability assessment and availability-based contract design.

5 Conclusions

This paper presents a methodological framework for assessing wind turbine reliability by integrating discrete-event simulation with statistical modeling techniques. The use of Simio enables the representation of multiple interacting failure processes, while Python-based tools support the identification and validation of appropriate probability distributions. As shown, an accurate characterization of failure modes and their statistical behavior improve the estimation of key performance indicators, particularly turbine availability. This aspect is especially relevant for supporting decision-making in availability-based contracts, which are critical in the power sector due to the potentially significant financial penalties associated with non-compliance. Furthermore, the inclusion of statistical validation enhances the robustness of the modeling approach by ensuring that failure dynamics are properly captured. Finally, the proposed framework can be extended in future work to evaluate the reliability and availability of entire wind farms, incorporating the interaction among multiple turbines and their connection to the grid.

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