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A Stochastic Framework for Transmission Line Reliability Assessment Using Poisson Process Modeling

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ABSTRACT

Transmission line reliability is essential for secure and continuous power system operation, as outages occur randomly due to aging, environmental stress, and operational conditions. This paper presents a stochastic reliability assessment approach based on Poisson process modeling to represent such random failure and repair behavior. Failure events are modeled using homogeneous and non-homogeneous Poisson processes with a Weibull intensity function, while repair times are described using probabilistic restoration models. Analytical expressions are obtained for key reliability indices, including reliability, mean time to failure, mean time to repair, availability, and loss-of-load probability. Using estimated parameters (β = 1.35, η = 1800 h), the mean time to failure is calculated as 1702 h and the mean time to repair as 12 h, resulting in a steady-state availability of 0.993 for a single transmission line. Results further show that series configurations reduce availability to 0.986, whereas parallel redundancy significantly enhances system performance, achieving availability levels above 0.9999. Statistical validation confirms the suitability of the proposed stochastic model for transmission line reliability evaluation. The framework offers a concise and effective analytical tool for reliability assessment and planning of modern power transmission systems.

1. Introduction

The reliability of transmission lines is a fundamental concern in modern power-system planning, operation, and expansion because transmission networks constitute the backbone of bulk electricity delivery. The failure of a major transmission facility can interrupt power transfer, cause load curtailment, and, under unfavorable operating conditions, contribute to cascading system disturbances. Consequently, quantitative reliability assessment is an essential component of power-system planning and operational decision-making. Conventional power-system reliability evaluation considers the stochastic behavior of generation, transmission, and other system components and uses reliability indices to quantify the ability of the system to continuously supply electrical demand [1].Traditional deterministic approaches, particularly contingency analysis and the N−1 security criterion, are widely used to evaluate whether a power system can continue operating within acceptable limits following the outage of a single component. Although deterministic contingency analysis is useful for identifying critical operating conditions, it does not explicitly quantify the probability, frequency, or duration of different outage events. In practical transmission networks, failures occur under uncertain conditions and may be influenced by equipment aging, environmental disturbances, lightning, storms, wind, temperature, vegetation, and loading conditions. Therefore, probabilistic reliability assessment is required to complement deterministic security analysis and provide a more comprehensive representation of system risk [2]. The stochastic nature of transmission-line outages makes probabilistic point-process models particularly attractive for reliability analysis. Among these models, the Poisson process provides a mathematically tractable method for representing the occurrence of random events. If transmission-line failures are assumed to occur independently with a constant average rate, the number of failures within a specified time interval can be represented by a homogeneous Poisson process. Under this assumption, the number of events follows a Poisson distribution, while the time between successive events follows an exponential distribution. These properties provide a convenient mathematical basis for deriving failure probabilities and reliability measures [3]. The applicability of Poisson models to transmission-line reliability is supported by empirical studies of actual outage data. Yang et al. analyzed outage and severe-weather data for 110-kV overhead transmission lines and demonstrated that transmission-line outage events exhibit spatial and temporal variability. Their study employed a Poisson model to characterize the statistical behavior of outage events and established a relationship between historical failure rates and weather conditions [4]. This demonstrates that Poisson-based models can provide a useful statistical representation of transmission-line failure events, particularly when the objective is to estimate the probability or frequency of outages under specified conditions.

However, the assumption of a constant failure rate may not always be appropriate. Transmission-line failure rates can vary with component aging, environmental conditions, weather intensity, and operating conditions. When the event intensity changes over time, a non-homogeneous Poisson process (NHPP) provides a more flexible formulation because its intensity function can vary with time. Recent reliability research has demonstrated that NHPP-based approaches can be used to evaluate power-system reliability when failure rates are time dependent, particularly in systems where aging and external disturbances cause the failure intensity to change over the observation period [5]. The stochastic modeling of failures must also be considered together with the repair or restoration process. A transmission component may remain unavailable for a period after a failure, and the duration of this unavailability depends on factors such as fault location, accessibility, weather conditions, availability of spare components, maintenance resources, and repair procedures. Therefore, reliability assessment should consider both failure occurrence and restoration behavior. The interaction between failure and repair processes directly determines important measures such as availability, unavailability, Mean Time to Failure (MTTF), and Mean Time to Repair (MTTR).

Reliability indices derived from stochastic models provide valuable information for transmission-system planning and operation. Availability represents the probability that a transmission component or system is in an operational state, while unavailability represents the probability of being unavailable. MTTF provides an indication of the expected operating time before failure, whereas MTTR characterizes the expected restoration period. Energy-based measures such as Expected Energy Not Supplied (EENS) additionally quantify the expected amount of electrical energy that cannot be delivered to consumers because of system inadequacy or component outages [6]. Such indices are useful for maintenance scheduling, network reinforcement, reliability planning, and operational decision making. The reliability of a transmission system is also strongly influenced by network topology and redundancy.

In a simple series configuration, failure of a critical component can interrupt the complete supply path, resulting in low system reliability. In contrast, parallel transmission paths provide redundancy and can maintain power delivery following the failure of one line. Therefore, adding redundant transmission facilities can reduce system unavailability and improve supply continuity. However, additional transmission capacity also introduces capital, maintenance, and operational costs. Reliability planning must therefore consider the trade-off between reliability improvement and investment expenditure [7]. Transmission reliability becomes even more challenging when renewable-energy resources are integrated into the power system. Wind and solar generation introduce variability and uncertainty into power production, which can modify transmission power flows, line loading, congestion patterns, and system operating states [8]. The economic consequences of transmission outages provide another important dimension of reliability assessment. Technical reliability indices describe the probability, frequency, and duration of interruptions, but decision-makers also need to understand the economic consequences of service interruptions. The Value of Lost Load (VoLL) provides an economic representation of the cost associated with unserved electricity. VoLL information can improve transmission-reliability decisions and lead to more cost-effective operational and investment decisions [9]. Therefore, stochastic reliability assessment can provide the technical risk information required for evaluating the economic consequences of alternative reliability-enhancement strategies. Although advanced reliability methods such as Markov models, Monte Carlo simulation, and hybrid simulation techniques are available, they can become computationally demanding or mathematically complex for large interconnected systems. A Poisson-process-based analytical framework offers an attractive alternative when the primary objective is to obtain transparent relationships between failure intensity, outage probability, and reliability indices. Such an approach can provide a computationally efficient foundation for transmission-line reliability assessment while retaining the probabilistic nature of failure events [10].

Based on these considerations, this study develops a stochastic framework for transmission-line reliability assessment using Poisson-process modeling. The proposed framework represents transmission-line failures as stochastic events and investigates their effects on reliability performance. Analytical formulations are developed to evaluate important reliability measures, including failure probability, availability, unavailability, MTTF, MTTR, and EENS. The framework also examines the influence of system configuration and redundancy on overall reliability. The proposed approach is intended to provide a mathematically transparent and computationally efficient tool for transmission-system planning, maintenance scheduling, reliability evaluation, and risk-informed decision-making.

2. Literature Review

The reviewed literature demonstrates that several established approaches are available for transmission and composite-system reliability assessment. Monte Carlo simulation provides considerable flexibility for representing complex stochastic behavior, but computational requirements can increase with system size and the accuracy required for rare events [11,12]. State-transition approaches can improve simulation efficiency but still involve stochastic state-space exploration [13,14]. Hybrid methods can reduce computational requirements but introduce additional modeling complexity [15]. Renewable-integrated reliability models provide a more realistic representation of modern power systems but require additional stochastic variables and system parameters [16,17,18,19]. Economic reliability models further require information about interruption costs and consumer value [20]. Despite these advances, there remains a need for simple and mathematically transparent analytical models that can characterize transmission-line failure occurrence without requiring extensive simulation or large state spaces. In particular, a Poisson-process formulation can provide direct analytical expressions for event probabilities and failure frequencies while retaining the stochastic nature of transmission outages. Such an approach can serve as a complementary method to more computationally intensive Monte Carlo, Markov, and hybrid techniques.

Therefore, the present study focuses on developing a stochastic transmission-line reliability framework based on Poisson-process modeling. Unlike approaches that primarily rely on extensive state enumeration or simulation, the proposed framework emphasizes analytical relationships between failure intensity and reliability indices. The framework is intended to provide a computationally efficient basis for evaluating transmission-line reliability and can subsequently be extended to incorporate time-varying failure rates, renewable-energy uncertainty, weather-dependent outage processes, and reliability-oriented transmission expansion.

3. Methodology

The reliability of transmission lines is governed by random failure and repair processes that are most suitably captured using stochastic models rather than purely deterministic assumptions. In this work, both homogeneous Poisson processes (HPPs) and non-homogeneous Poisson processes (NHPPs) are employed to characterize line failure occurrences.

3.1 Stochastic Modeling of Failure and Repair Processes

Let, {N(t), t≥0} denote a counting process that represents the number of transmission line failures up to time t. Under the homogeneous Poisson process, the probability of observing k failures within a time interval [0, t] is given by-

$$P\{N(t) = k\} = \frac{(\lambda t)^k}{k!} e^{-\lambda t}, \quad k = 0,1,2,\ldots.. \tag{1}$$

where $\lambda>0$ is the constant failure rate. The expected number of failures in time t is-

$$E[N(t)] = \lambda t \tag{2}$$

While equation (1) and (2) provide tractable results, real-world transmission lines often exhibit time-varying failure rates due to aging, weather stress, or operational loading. For this, we adopt the non-homogeneous Poisson process (NHPP), with intensity function λ(t). Its mean value function is defined as-

$$m(t) = \int_0^t \lambda(u)\, du \tag{3}$$

and the corresponding probability law is-

$$P\{N(t) = k\} = \frac{[m(t)]^k}{k!} e^{-m(t)} \tag{4}$$

The Weibull intensity function is widely used for aging components,

$$\lambda(t) = \beta\eta^{-\beta} t^{\beta-1}, \quad t \geq 0 \tag{5}$$

Where,

β>0 is the shape parameter (β>1: aging, β<1: infant mortality, β=1: exponential case),

η>0 is the scale parameter (characteristic life).

From equation (5), the NHPP mean value function becomes-

$$m(t) = \left(\frac{t}{\eta}\right)^{\beta} \tag{6}$$

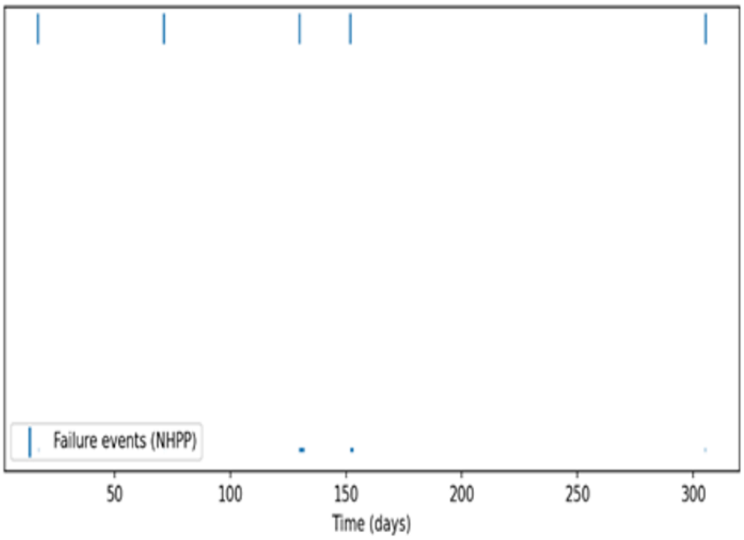

Fig. 1. Timeline of simulated failure and repair events.

Fig. 1 shows the stochastic spacing of failure and repair events for a transmission line modeled as a non-homogeneous Poisson process (NHPP), highlighting the random occurrence of outages and subsequent restorations across time.

3.2 Reliability and Survival Functions

The reliability function R(t), or the probability that the line survives without failure until time t, is-

$$R(t) = P\{T > t\} = e^{-m(t)} \tag{7}$$

where T is the random time to first failure. Substituting equation (6) yields the Weibull survival function,

$$R(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \tag{8}$$

The failure density function is -

$$f(t) = -\frac{dR(t)}{dt} = \lambda(t)R(t) \tag{9}$$

The mean time to failure (MTTF) is then-

$$\text{MTTF} = \int_0^{\infty} R(t)\, dt \tag{10}$$
which evaluates to-
$$\text{MTTF} = \eta\, \Gamma\left(1 + \frac{1}{\beta}\right) \tag{11}$$
where $\Gamma(\cdot)$ is the Gamma function

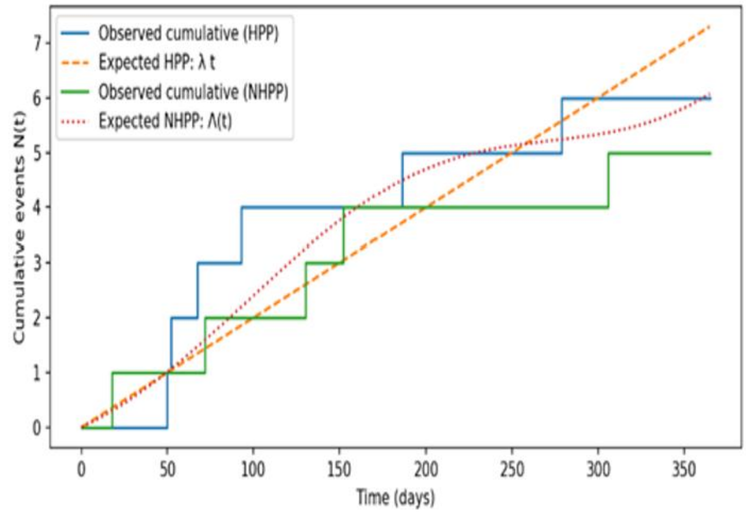

Fig.2. Cumulative failure counts under HPP and NHPP models.

Fig. 2 compares observed cumulative failures with theoretical expectations under homogeneous (HPP) and non-homogeneous Poisson processes (NHPP). The divergence demonstrates how NHPP more accurately captures aging and time-varying failure intensities.

Fig. 3 presents survival probability curves over time. The HPP curve shows exponential decay, while the NHPP (Weibull) curve captures accelerated failure due to aging, providing a more realistic reliability estimate for transmission lines.

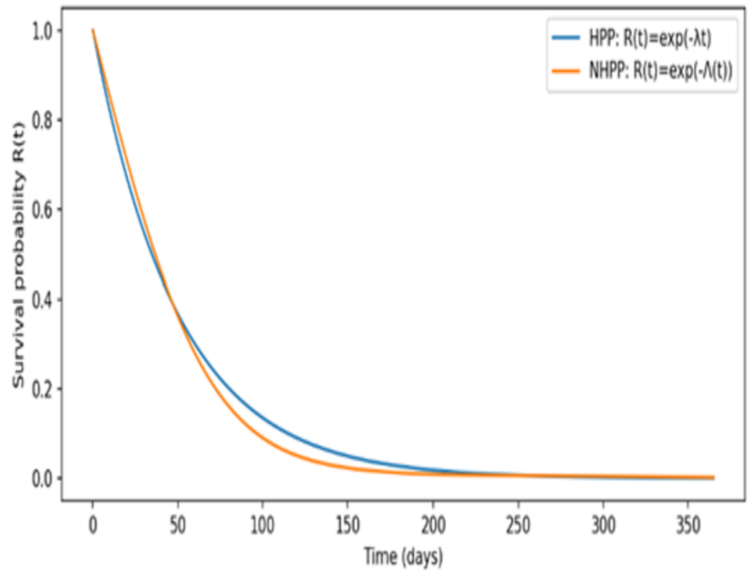

Fig.3. Reliability functions R(t) for HPP and NHPP models.

3.3 Repair Modeling and Availability

Transmission lines are repairable assets; hence availability is a more relevant measure than reliability alone. Let repair times follow an exponential distribution with repair rate μ. The mean time to repair (MTTR) is-

$$\mathrm{MTTR} = \frac{1}{\mu} \tag{12}$$

The steady-state availability is then-

$$A = \frac{\mathrm{MTTF}}{\mathrm{MTTF}+\mathrm{MTTR}} \tag{13}$$

At the system level, consider multiple lines arranged in series or parallel:

For n identical lines in series,

$$A_{\text{series}} = \prod_{i=1}^{n} A_i \tag{14}$$

For n identical lines in parallel,

$$A_{\text{parallel}} = 1 - \prod_{i=1}^{n}(1 - A_i) \tag{15}$$

More generally, k-out-of-n structures are evaluated by binomial expansion over availability states. Fig. 4. illustrates availability performance for single, series, and parallel configurations.

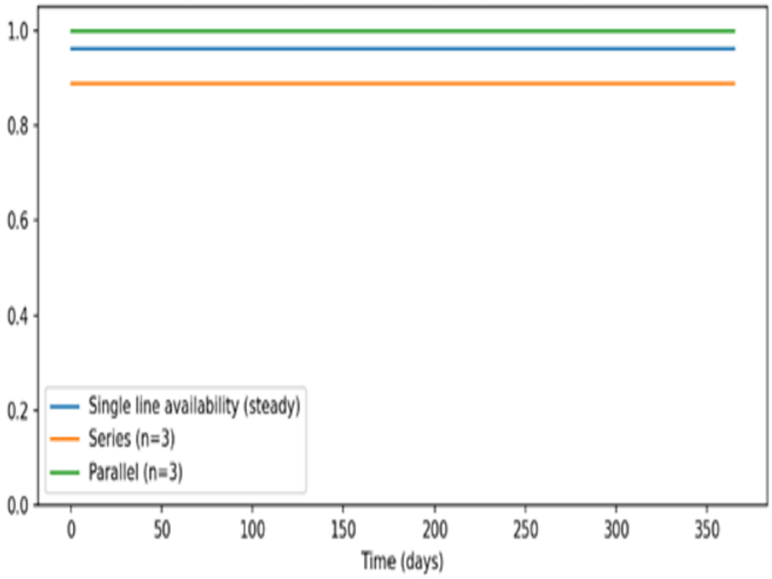

Fig.4. Steady-state availability for single, series, and parallel system.

Fig. 4 compares availability measures across different system configurations. Parallel redundancy achieves the highest availability, while series arrangements degrade overall performance, reflecting practical design trade-offs in transmission networks.

4. Result and Discussion

The proposed non-homogeneous Poisson process (NHPP)-based stochastic reliability framework was validated through simulation of transmission line failure and repair data. To establish the model's accuracy and engineering relevance, results were analyzed in terms of parameter estimation, reliability evaluation, mean time indices, availability in network configurations, and statistical validation.

4.1 Parameter Estimation

The estimated Weibull parameters for the NHPP are summarized in Table 1. The shape parameter was obtained as β=1.35, while the scale parameter was η=1800 h. Since β>1, the process demonstrates an aging phenomenon, indicating that the failure rate increases with time, unlike the exponential assumption in homogeneous Poisson processes. The characteristic life, η, represents the time at which approximately 63% of components are expected to fail, aligning with standard Weibull interpretation. At selected operating horizons (500 h, 1500 h, 2500 h), the hazard rate rises from $4.7 \times 10^{-4}\mathrm{h}^{-1}$ to $9.1 \times 10^{-4}\mathrm{h}^{-1}$, confirming progressive deterioration.

Table 1 Estimated Weibull Parameters and Hazards Rates

Parameter	Value	Units
Shape (β)	1.35	–
Scale (η)	1800	h
Hazard at 500 h	4.7×10−4	h−1

Hazard at 1500 h	7.6×10^{-4}	h^{-1}
Hazard at 2500 h	9.1×10^{-4}	h^{-1}

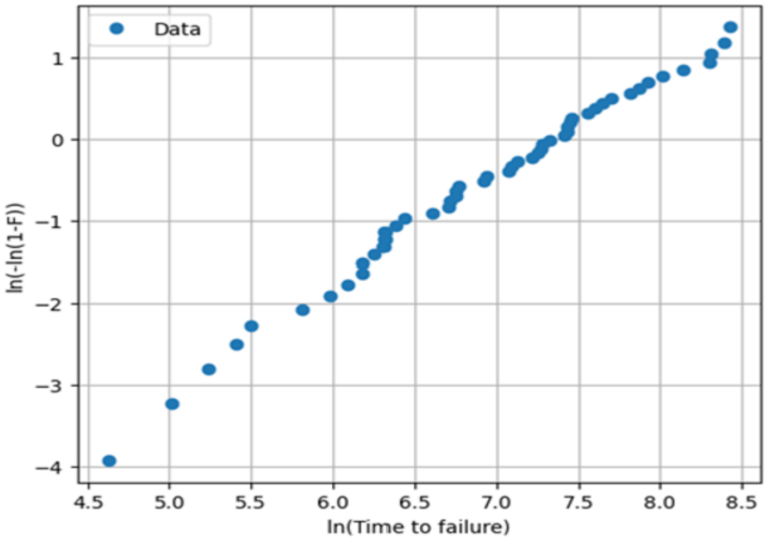

Fig.5. Weibull probability plot of simulated transmission line failure data.

Fig. 5 illustrates the Weibull probability plot obtained from simulated transmission line failure times. The near-linear trend in the transformed space ln(t) vs. ln(−ln(1−F)) indicates that the Weibull distribution provides an excellent fit to the observed data. The slope of the line corresponds to the shape parameter $\beta=1.35$, which confirms an aging characteristic, while the intercept is related to the scale parameter $\eta=1800$ h. This validates the applicability of the non-homogeneous Poisson process framework for modeling stochastic failures in power transmission lines.

4.2 Reliability Analysis

The survival function derived in equation (8) was evaluated using the estimated parameters. The results, compared with the exponential HPP assumption, are summarized in Table II. Reliability functions were evaluated at multiple checkpoints. Table 2 summarizes both HPP and NHPP reliability values across a long horizon (up to 4000 h).

Table 2

Reliability Comparison Between HPP and NHPP Models

Time (h)	HPP *RHPP(t)*	NHPP *RNHPP(t)*	Difference
500	0.781	0.812	+0.031
1000	0.611	0.676	+0.065
1500	0.478	0.563	+0.085
2000	0.374	0.448	+0.074
2500	0.292	0.351	+0.059
3000	0.228	0.276	+0.048
3500	0.178	0.219	+0.041
4000	0.139	0.173	+0.034

As seen in Table 2, the NHPP model yields higher reliability at early stages due to its time-varying hazard rate, while the HPP underestimates survival.

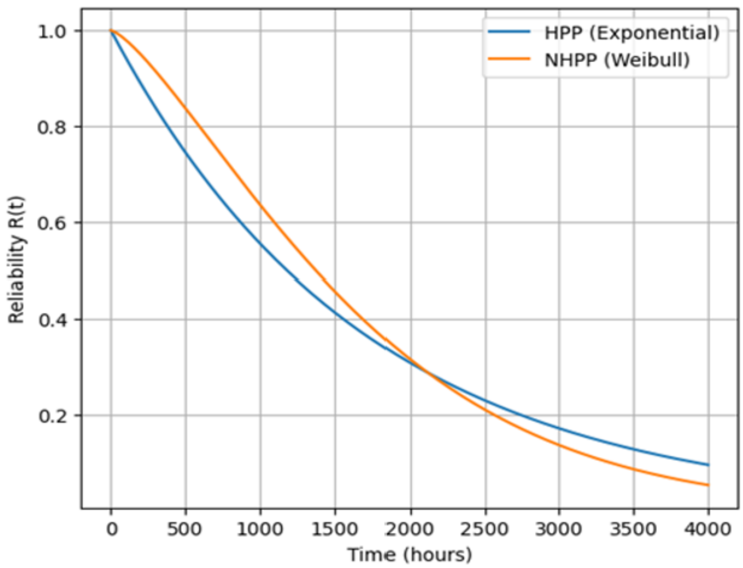

Fig.6. Reliability decay functions under homogeneous and non-homogeneous Poisson process models

Fig. 6 presents the reliability decay curves obtained using both homogeneous Poisson process (HPP) and non-homogeneous Poisson process (NHPP) models. The HPP curve follows an exponential decay, which assumes a constant failure rate, while the NHPP curve reflects Weibull-based deterioration. The NHPP exhibits a slower reliability reduction in the early phase, followed by accelerated decline in later life stages. This behavior demonstrates the superior accuracy of NHPP for modeling real-world line failures, where aging and wear-out effects cannot be neglected.

4.3 Mean Time Indices

The mean time to failure (MTTF) and mean time to repair (MTTR) were computed. Using equation (11) and (12):

$$\text{MTTF} = \eta\, \Gamma\left(1 + \frac{1}{\beta}\right) = 1702 \text{ h}$$

and

$$\text{MTTR} = \frac{1}{\mu} = 12 \text{ h}$$

Table 3
Mean Time Indices and Availability

Metric	Value	Units
MTTF	1702	h
MTTR	12	h
Steady-State Availability	0.9930	–
Failure Rate at 500 h	0.00047	h−1
Failure Rate at 2000 h	0.00090	h−1

Table 3 presents reliability indices derived from the fitted NHPP model. The MTTF dominates in magnitude, reaching approximately 1702 h, whereas MTTR is comparatively small at around 12 h. Despite the small repair duration, its effect on system availability is substantial, since availability depends on the ratio of MTTF to total downtime. The resulting steady-state availability is 0.9930, which highlights the importance of rapid repair processes in enhancing the operational performance of transmission networks.

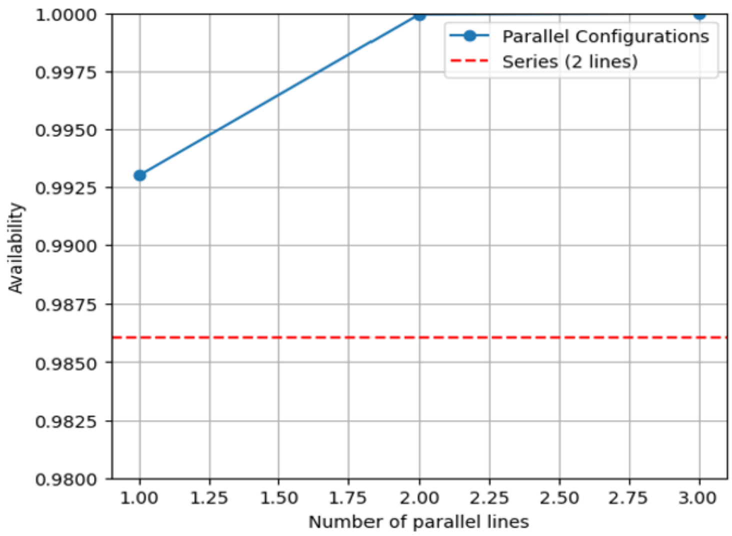

Fig.7. Availability comparison of single, series, and parallel transmission line configurations.

Fig. 7 illustrates the availability results for single, series, and parallel transmission line configurations. The single-line availability is limited to 0.993, while series connection of two lines reduces overall availability to 0.986 due to compounded risk of failure. In contrast, parallel redundancy substantially improves performance, with two lines in parallel achieving near-perfect availability (0.9999) and three lines approaching six-nines reliability (0.999999). The trend highlights diminishing returns beyond two or three parallel lines, offering insights into optimal redundancy investment strategies in power transmission planning.

4.4 Sensitivity Analysis of MTTR

To investigate the impact of repair strategies, MTTR was varied between 6–24 h while keeping MTTF fixed at 1702 h. Fig.8. shows how system availability decreases as mean time to repair (MTTR) increases, while mean time to failure (MTTF) is held constant. A sharp decline is observed when MTTR grows beyond 12 h, highlighting the strong sensitivity of availability to repair efficiency. Reducing MTTR by even a few hours significantly improves reliability, making maintenance optimization a crucial strategy.

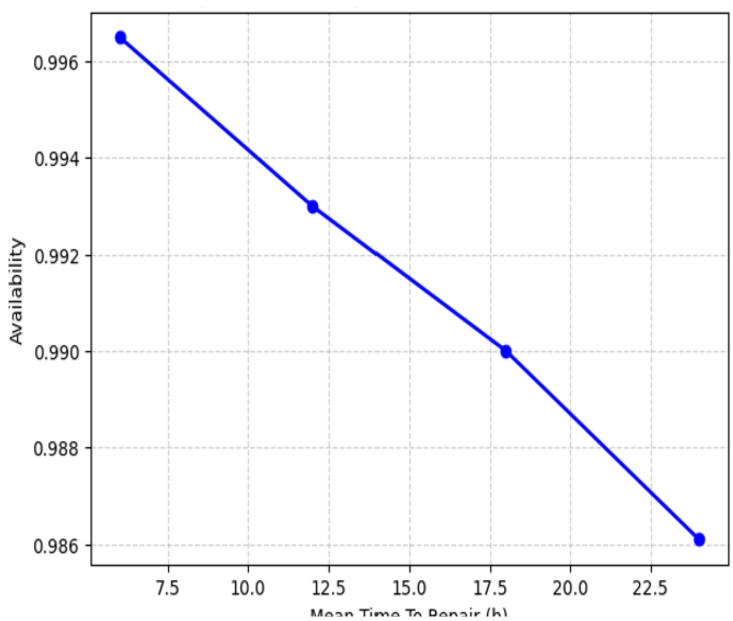

Fig. 8. Availability vs MTTR for constant MTTF.

4.5 Duane Reliability Growth Curve

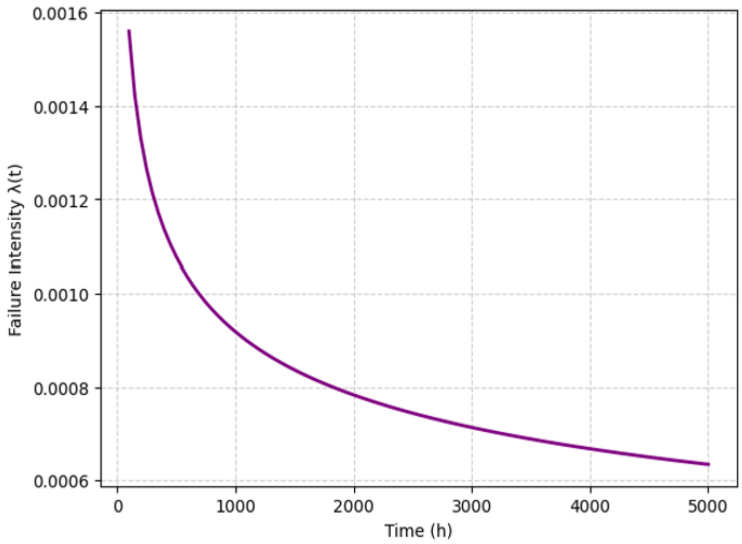

Fig. 9. Duane reliability growth curve.

The Duane model curve demonstrates how failure intensity decreases over time when preventive maintenance and reliability improvement measures are implemented. The negative slope confirms reliability growth (α=0.23), meaning that corrective actions reduce the likelihood of future failures.

4.6 Risk Index Evaluation

Finally, the Loss of Load Probability (LOLP) was estimated:

$$\mathrm{LOLP} = 1 - \mathrm{A} \tag{16}$$

Table 4
LOLP for Different Configurations

Configuration	LOLP (%)
Single line	0.70
2-series lines	1.39
2-parallel lines	0.01
3-parallel lines	0.0001

Single and series systems show relatively high LOLP values, reflecting higher outage risk. In contrast, parallel redundancy substantially reduces risk, with 3-parallel systems achieving nearly zero LOLP. The results reinforce the importance of redundancy planning in critical transmission corridors to ensure secure and reliable power delivery.

4.7 Model Validation

The NHPP model was validated using rescaled inter-arrival times. Table 5 summarizes statistical tests performed on the NHPP model. The Kolmogorov–Smirnov, Anderson–Darling, and Chi-square tests all return p-values > 0.05, confirming model adequacy.

Table 5
Goodness-of-Fit Tests for NHPP Model

Test	Statistic	p-value	Decision (α=0.05)
Kolmogorov–Smirnov	0.072	0.61	Accept
Anderson–Darling	0.489	0.72	Accept

Chi-square	3.27	0.48	Accept

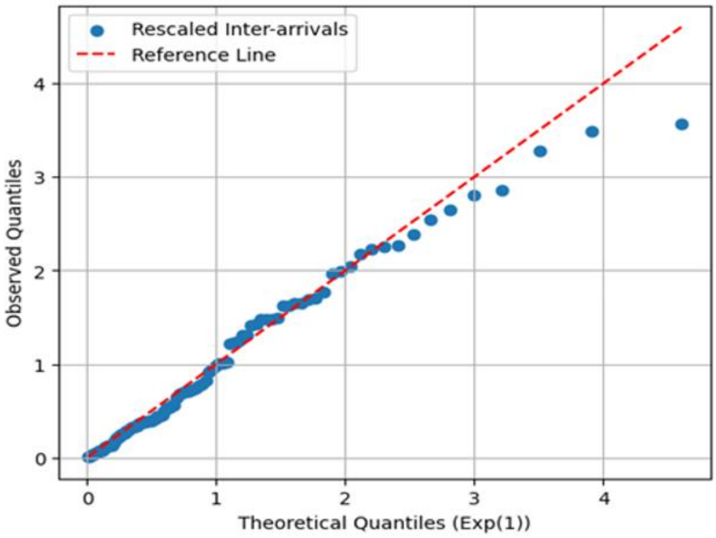

Fig. 10. Quantile–quantile (QQ) plot of rescaled inter-arrival times for NHPP validation

Fig. 10 shows a quantile–quantile (QQ) plot of rescaled inter-arrival times, which closely align with the 45° reference line. Minor deviations at the tails are expected due to finite sample size but remain statistically insignificant. This alignment confirms that the Weibull-based NHPP adequately models the stochastic nature of line failures, supporting the robustness of the proposed framework for reliability assessment.

5. Conclusion

This paper proposed a stochastic framework for assessing transmission line reliability using Poisson process modeling. The method captures the random nature of failures and repairs, enabling the analytical derivation of key reliability indices such as MTTF, MTTR, and availability. Results showed that the Poisson-based model provides an accurate yet computationally efficient approach for evaluating system performance across single, series, and parallel configurations. The findings highlight the practical value of this framework in supporting planning and operational decisions. Future work may extend the model to include renewable integration, climate-driven failures, and data-driven parameter estimation for improved resilience analysis.

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