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Markov model-based reliability and availability analysis: A case study of mando-Shiroro 330kV power transmission network

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Abstract

The transmission of electrical energy is one of the most significant infrastructural undertakings. Traditional manual routing methods are still widely used in the sector despite its rapid expansion and high project costs. These methods are inefficient, expensive and time-consuming when compared to more current reliability evaluation techniques. The results of the findings revealed that the least amount of power outage for planned and unplanned as 95.4 and 14.2 hours was recorded in 2022 as indicated from the data sheet. In 2022, the highest recorded operational hours (298.99 hours) were achieved with a low failure rate (171.45 hours) and a high repair rate (8.15 hours). The average LOEE and LOLE recorded are 498.29 and 499.113 MW and 562.25 and 844.90 Mw/year for the year 2022 and 2023. The most reliability findings came from 2022, with MTTF, MTTR, and MBTF values of 101.67, 87.62, and 24. 23. Also, Bus load A (100 MW) had the best operating reliability (0.98), according to the Roy Billinton Test 6 Bus System Performance Assessment. The RBTS bus's simulation results showed an average EENS of 37.96 MW, with a matching system reliability of 90.54% respectively.

Keywords: Markov; Reliability; Availability; Power Transmission Network; Mando-Shiroro

1. Introduction

Power transmission networks are the foundation of the contemporary energy infrastructure in the world, and they are essential to maintaining the stability and dependability of the electrical supply. Many studies have been conducted on the examination of transmission network reliability, covering topics such network architecture, component failure analysis, and system performance evaluation [1], Emphasized the need for long-term planning for electric power systems, stressing the use of linear programming for network analysis and the investigation of bulk power transmission network designs. In the meanwhile, [2] stressed the need for better techniques to measure and increase system resilience and presented a spatial-temporal reliability and damage assessment method to estimate the impact of hurricanes on transmission networks. Globally, networks for transmitting electricity constitute a significant portion of the infrastructure sector [3]. Since power lines are needed to move power from power plants to transformer substations and then to consumers, they serve as the foundation of any power transmission network. The most popular kinds are Overhead Power Transmission Lines (OHPTL) because of their affordability, simplicity of upkeep, and superiority over alternative techniques like underground cables or microwave transmission [4] .

With the integration of renewable energy and energy storage gaining prominence, evaluating their impact on transmission network reliability has become crucial. The study by [5] addressed the sizing of battery energy storage systems (BESS) alongside demand response and dynamic thermal rating systems to improve power grid security. This emphasizes the significance of analyzing integrated strategies involving renewable sources, storage, and demand response to enhance network reliability [6].

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In Nigeria, a nation striving for improved energy security, the reliability of transmission systems takes on even greater importance[7]. The work by[8] assessed the reliability of the Nigerian transmission system and highlighted the need for more effective reliability indices to address unpredicted outages. Therefore, considering the unique challenges faced by Nigeria's power infrastructure, such as insufficient maintenance and distribution losses, researching the reliability of specific voltage levels, such as 330KV, becomes vital. This research will not only contribute to identifying vulnerabilities but also guide the implementation of measures to enhan ce reliability, contributing to the country's efforts to modernize its energy landscape.

By building upon the insights from these studies, this research aims to develop tailored reliability metrics, assess the impact of renewable energy integration, and enhance the resilience of Nigeria's 330KV transmission system. Through this, the study seeks to address gaps in the understanding of transmission system performance and contribute to the nation's pursuit of a reliable and sustainable energy infrastructure.

2. Materials and methods

2.1. Materials/Tools

The chronological failure history of the Mando-Shiroro 330kV transmission network was collected and based on this data, reliability indices are determined. The procedure adopted in this section applies to the transmission network of Mando sub-station, Transmission Company of Nigeria. To properly carry out the Reliability evaluation of Mando-Shiroro 33kV Transmission network using Markov Chain analyses, this section outlines the material needed for the analyses as presents in the Table 1. Also, the data from the operation logbooks of the 330kV Mando control room was collected from Months of January to December for the year 2022 and 2023 as presented in Tables 2 and 3 respectively.

Table 1 Equipment and their uses in the Markov model-based reliability and availability Analysis of Mando-Shiroro 330kV power transmission network.

SNO	Equipment/Tools	Model Specification	Uses
1.	MATLAB®	Version 2023a	Used for modelling of reliability analysis
2.	Data collection	Sources from 330kV Mando transmission station	Used for running the reliability analysis
3.	Computer	HP 1 TRB, 500 GB RAM	Used for installation of MATLAB Software

Table 2 Raw data sheet results of Mando-Shiroro 330kV transmission network year 2022.

Schedules	**Forced shut down**				**Planned shut down**			
Month	**Time In (hr)**	**Time Out (hr)**	**Outrage Duration (hr)**	**Energy Loss (MWh)**	**Time In (hr)**	**Time Out (hr)**	**Outrage Duration (hr)**	**Energy Loss (MWh)**
January	**11:54**	**12:52**	**0.98**	**215.992**	**11:13**	**15:13**	**4.38**	**0**
February	0	0	0	0	0	0	0	0
March	0	0	0	0	0	0	0	0
April	0	0	0	0	0	0	0	0
May	18:17	16:31	2.7	0	0	0	0	0
June	02:18	18:44	15.66	85.8	2:16	16:31	14.23	14.23
July	16:07	22:34	12.31	2450.5	17:51	18:44	0.88	0.88

August	11:28	22:34	10.87	2173.34	0	0	0	0
September	17:03	16:27	95.40	0	13:05	14:17	1.20	240
October	0	0	0	0	0	0	0	0
November	13:29	13:49	1:51	0	0	0	0	0
December	10:10	15:14	7.83	562.52	0	0	0	0
Total	99.66	136.85	18.38	5488.15	44.08	64.05	20.69	255.11

Table 3 Raw data sheet results of Mando-Shiroro 330kV transmission network year 2023**.**

Schedules	**Forced shut down**				**Planned shut down**			
Month	Time In (hr)	Time Out (hr)	Outrage Duration (hr)	Energy Loss (MWh)	Time In (hr)	Time Out (hr)	Outrage Duration (hr)	Energy Loss (MWh)
January	12:30	16:40	0.42	0	0	0	0	0
February	12:59	13:21	0.37	107.07	09:05	17:50	428	21457
March	11:03	07:34	2.21	1285.35	0	0	0	0
April	19:03	18:00	69.02	0	11:34	15:32	3.97	0
May	0	0	0	0	0	0	0	0
June	00:07	16:07	1318.03	67985.03	09:34	18:33	8.98	0
July	18:14	18:45	0.52	2450.5	0	0	0	0
August	21:27	18:03	117.6	0	0	0	0	0
September	0	0	0	0	0	0	0	0
October	0	0	0	0	0	0	0	0
November	0	0	0	0	0	0	0	0
December	18:14	18:41	0.52	562.52	0	0	0	0
Total	112.57	125.91	1508.69	72390.5	29.73	51.15	440.95	2145.7

2.2. Method

The Mando-Shiroro 330kV transmission network was modelled using mathematical model based on continuous time Markov Chain analysis to check the availability and reliability of the transmission network for the year 2022 and 2023. The transmission network work was modelled based on the two-state Markov process with constant failure and repair rates i.e. transition rates. Furthermore, Roy Billinton Test 6 Bus System Performance assessment was conducted to check the check in the reliability and expected energy not used (EENS).

2.2.1. Markov Chain analysis state model

The Markov technique is a state space approach to reliability evaluation, where the power system is defined as existing in any one-of a few finite system states at a particular instant in time. Throughout the lifetime of the power system, transitions at certain rates will be made between power system states as components fail and are repaired, and a certain probability of existing in a particular state can be derived from these transition rates where, the occurrences of such failures being independent of their own failure and repair rates. Also, developing mathematical equations used in solving the probabilities and analyzed to find the reliability indices, MTTF (Mean Time To Failure), MTBF (Mean Time Before Failure), MTTR (Mean Time To Repair) and Availability to provide insight on the Mando-Shiroro transmission network. Equations 1 to 18 present the equations that govern transitions for

Transmission Line failures between the normal and failure statuses. Figure 1 presents the Markov chain analysis state model developed for the Mando-Shiroro 330KV transmission network.

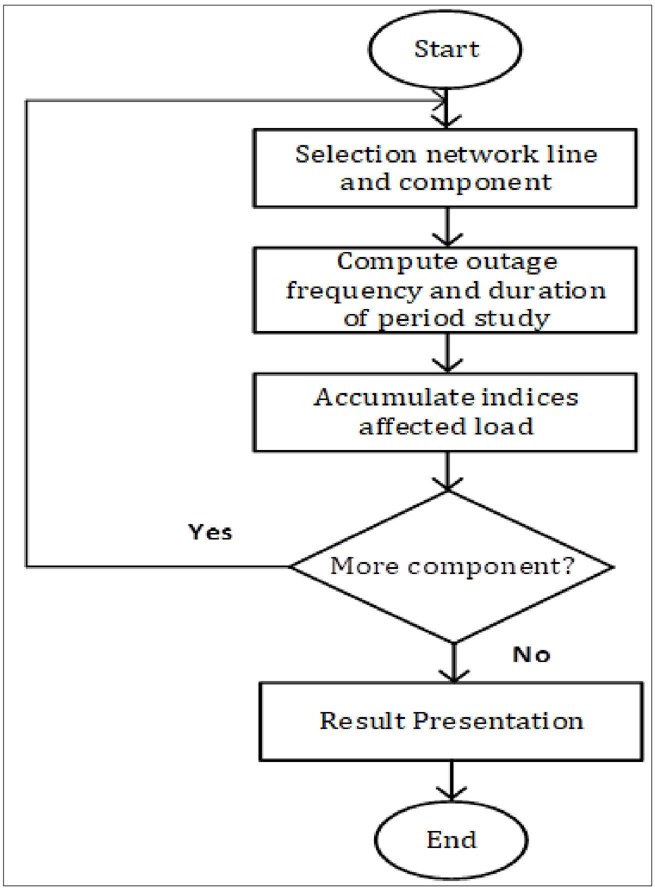

Figure 1 Markov Chain analysis state model.

The mathematical model developed for the Markov chain analysis on the probability state of the Mando-Shiroro transmission network is shown in Equation 1.

$$\frac{dp_a(t)}{dt} = p_a(t)A_a \qquad \text{..............................} \qquad (1)$$

Where $p_a(t)$ is the row vector that contains normal and failure status probabilities i.e. $p_a(t)$ and $q_a(t)$ as shown in Equation 2.

$$p_a(t) = [p_a(t),\ q_a(t)] \qquad \text{..............................} (2)$$

Furthermore, the normal and failure status probabilities add up to 1 as in Equation 3.

$$\text{Also} p_a(t) + q_a(t) = 1 \qquad \text{..............................} (3)$$

Where $0 \leq p_a(t) \geq 1$ and $0 \leq q_a(t) \geq 1$

In addition, A_a is the transition intensity matrix as expressed in Equation 4:

$$A_a = \begin{bmatrix} -\lambda_a & \lambda_a \\ \mu_a & -\mu_a \end{bmatrix} \qquad \text{..............................} (4)$$

The initial condition represents the probability of normal status set to one and the probability of failure status set to zero is as present in Equation 5.

$$p_a(0) = [1\ 0] \quad \text{.............................} (5)$$

The solution to the above differential equations gives the probabilities of normal and failure statuses depicted in Equations 6, 7 and 8 respectively.

$$p_a(t) = \frac{\mu_a}{\lambda_a+\mu_a} + \frac{\lambda_a}{\lambda_a+\mu_a} \exp\left(-(\lambda_a + \mu_a)t\right) \quad \text{.............................} (6)$$

$$p_a(t) = 1 - q_a(t) \quad \text{.............................} (7)$$

$$q_a(t) = \frac{\lambda_a}{\lambda_a+\mu_a} - \frac{\lambda_a}{\lambda_a+\mu_a} \exp\left(-(\lambda_a + \mu_a)t\right) \quad \text{.............................} (8)$$

Where λ_a= failure rate

μ_a= repair rate

If only long-term status probabilities are of interest, the normal and failure status probabilities are expressed in Equations 9 and 10 as follows:

$$p_a(\infty) = \frac{\mu_a}{\lambda_a+\mu_a} \quad \text{.............................} \quad (9)$$

$$q_a(\infty) = \frac{\lambda_a}{\lambda_a+\mu_a} \quad \text{.............................} (10)$$

The reliability indices will be calculated using the following formulae in Equation 10, 11 and 12 respectively.

$$\lambda = \frac{N}{\sum_{i=1}^{N} T_{ui}} \quad \text{.............................} \quad (10)$$

$$r = \frac{\sum_{i=1}^{N} T_{di}}{N} \quad \text{.............................} \quad (11)$$

$$f = \frac{N}{\sum_{i=1}^{N} (T_{ui} + T_{di})} \quad \text{.............................} (12)$$

Where T_{ui}= uptime

T_{di}= downtime

N = Number of outages over time

Using the methodology described above, for each critical 330kV feeder field data i.e. number of outages, outage duration per year basis is collected, the MTBF, MTTR, MTTF, failure frequency, Availabilities and Unavailability are computed with their formulars as presented in Equations 13 to 18 respectively [9].

$$MTBF = \frac{Total\ availbe\ operating\ time}{Number\ of\ failure} \quad \text{.............................} (13)$$

$$MTTR = \frac{Total\ down\ time}{Number\ of\ Repair} \quad \text{.............................} \quad (14)$$

$$MTTF = MTBF - MTTR \quad \text{.............................} \quad (15)$$

$$Frequncy\ failure = \frac{1}{MBTF+MTTR} \quad \text{.............................} \quad (16)$$

$$Availibility = \frac{MTBR}{MBTF+MTTR} \quad \text{.............................} \quad (17)$$

$$Unavailibility = \frac{MTTR}{MBTF+MTTR} \quad \text{.............................} \quad (18)$$

- Assumptions of Markov Chain analysis state model

Running a Markov-based reliability and availability analysis of Mando-Shiroro 330kV transmission network typically involved the following assumptions:

- The model was run as steady state three state system (Operational, failure and repair).
- The model was discrete in nature.
- The system simplifies the analysis of past transition.
- The transition probability between states (Operational to failure and failed to operational) is constant over time.
- The failure and repair times assumed to follow exponential distribution.
- The system components considered are transmission lines.
- System reliability and availability are typically measured using metrics such as Mean Time Between failure (MTBF), Mean Time To Repair (MTTR), Mean Time To Failure (MTTF) and availability (A).
- Individual components failure is assuming to be independent unless there are specific correlations (e.g., due to common causes like weather condition, age-related failures)

2.2.2. Roy Billiton test 6 bus system performance assessment

A reliability evaluation technique called the Roy Billinton Test (RBT) is used to gauge how well power network function, especially in terms of their capacity to provide electricity under a range of circumstances [10]. The RBT aids in determining the operational efficacy and dependability of the transmission infrastructure when it is applied to the Mando-Shiroro power transmission network. The assessment involves simulating different scenarios, including equipment failures, maintenance schedules, and load variations, to determine the likelihood of power outages and the overall system reliability. Key performance indicators, such as system average expected energy not supplied (EENS) in MW and system reliability (%), are analyzed. The modelling and analysis of IEEE-6 bus system using Markov model has resulted that the probability of acceptable states is decreasing as time scale increases and probability of unacceptable state is increasing as time scale increases as shown in Figure 2. Frequency and duration values of each state have resulted in the frequency and duration values decrease as state increases.

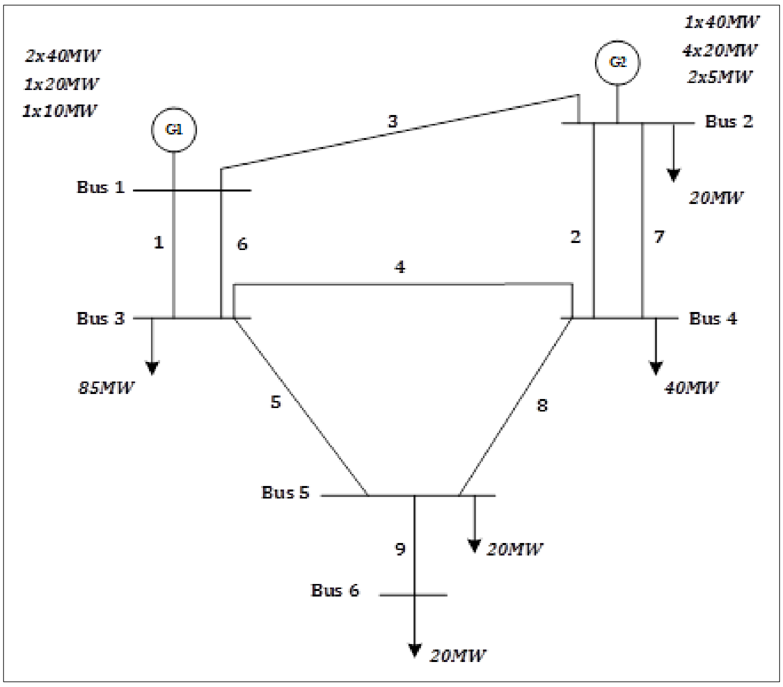

Figure 2 Single line diagram of the IEEE 6-BUS RBTS

Figure 3. Presents the method carried out to performed assessment of Roy Billinton 6 Bus Test System on the Mando-Shiroro 330kV transmission network.

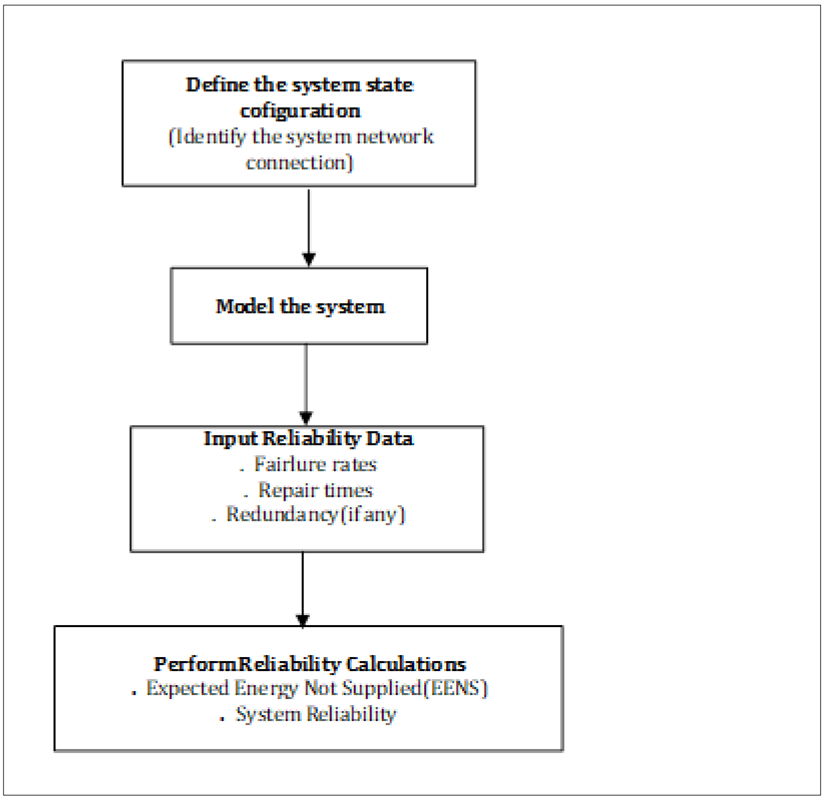

Figure 3 Methodological block flow diagram for Roy Billinton Test 6 Bus system Performance assessment

One standard used to assess the reliability of electricity systems is the Roy Billinton Test. It offers a framework for evaluating a power network's reliability indices and simulating its performance under various conditions [11]. Table 4 presents the assumption parameters used in running Roy Billinton Test 6 Bus System Performance Assessment using MATLAB environment.

Table 4 Assumption Parameters for Roy Billinton Test 6 Bus System Performance Assessment

Parameters	**A**	**B**	**C**	**D**	**E**	**F**
Bus number	1	2	3	4	5	6
Bus capacity (MW)	100	50	75	60	80	40

3. Results and discussion

This section presents the relevant results and discussion carried out on this research work reliability evaluation of Mando-Shiroro 330kV transmission network using Markov chain analysis.

3.1. Markov chain analysis of Mando-Shiroro 330kV transmission network

This sub section presents the results of reliability, operational (Availability), failure and under repair (Unavailability) rate for the 330kV Mando-Shiroro power transmission network as depicted in Figure 4.

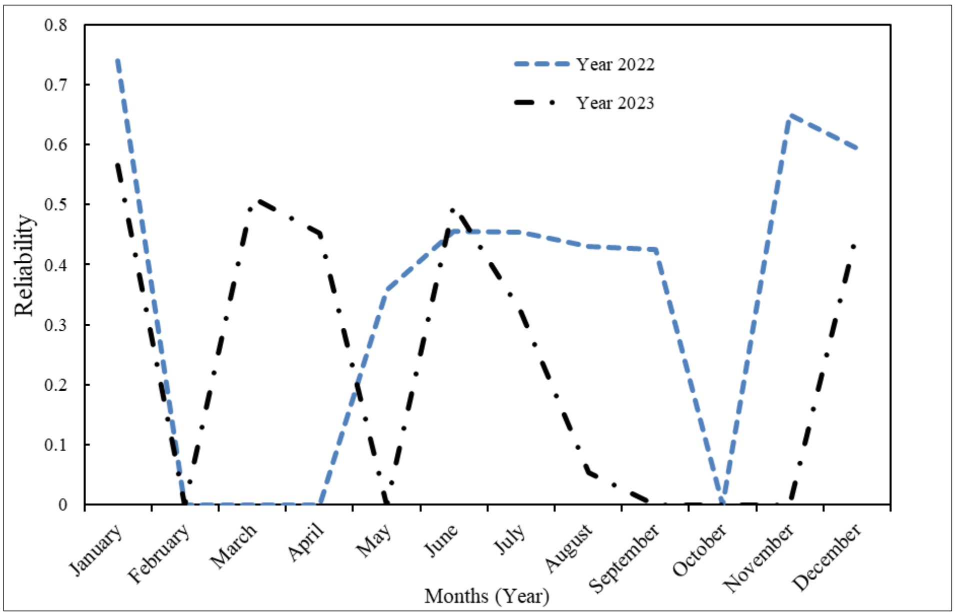

Figure 4 Reliability for monthly analysis year 2022 and 2023 using Markov chain analysis

The reliability projection for many months in 2022 and 2023 is shown in Figure 4. Based on Figure 4. It is evident that in 2022, reliability peaked in January with a value of 0.74. From there, it fell to zero in February, March, and April before rising steadily from May (0.357). June and July then remained stable from June to September before falling to zero in October, and reliability reappeared in November and December with values of 0.65 and 0.594. Nonetheless, the same pattern was seen in Figure 4 for the year 2023, with the maximum highest reliability of 0.566 being attained in January. January exhibits greater dependability, which could be explained by the fact that it was the first month of the year and that end-of-year maintenance was in place. This aligns well with the research conducted by Bo, et al. [12] from their research showed that the highest reliability of 0.987 was recorded in January.

However, the total results showed that January had the best reliability rate of any month, with a very good rate. The highest reliability rate was recorded in the year 2022, at 0.74, compared to the lowest in the year 2023, at 0.556. Additionally, the average dependability for the years 2022 and 2023 is 0.56 and 0.35, respectively, indicating that the year 2022 has a 0.205 higher reliability rate. This is because the year 2022 has a consistently lower component failure rate.

3.1.1. Probability rate of Repair, failure, LOLE and LOEE

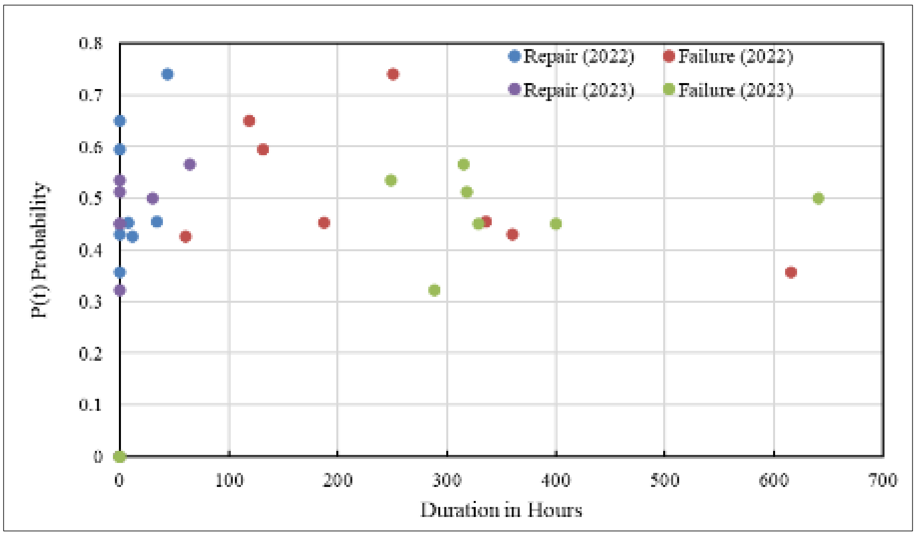

Figure 5 Probability of failure and repair rate of Mando-Shiroro 330kV transmission network

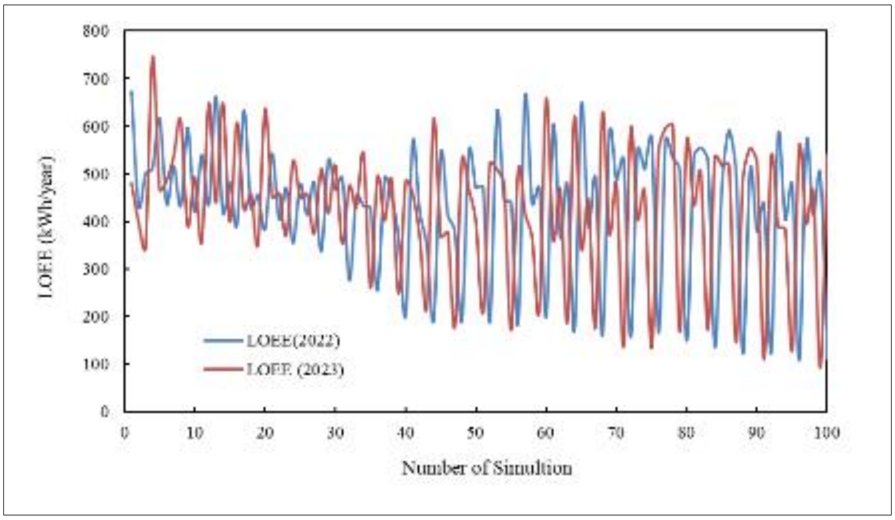

Figure 6 Loss of energy expected of Mando-Shiroro 330 kV Transmission network

Figure 5 presents the results of probability of failure and repair rate for the year 2022 and 2023 on Mando-Shiroro 330kV transmission network. It can be observed from Figure 5 that the maximum repair rate occurred at 0.74 probability (43.5 hours), while the lowest at 0.1 hours, similarly, the minimum repair rate recorded at 0.1 hours for the year 2022. However, it can be noticed from Figure 5; that year 2023 shows that at maximum, 64.5 hours was utilized for repairing at the probability rate of 0.566, while the minimum repairing rate is 0.00 hours at 0.332 chance probability. Moreover, the maximum failure rate occurred at 315 hours (0.566 probability) and minimum of 288 hours recorded for the year 2023. This may be failure rate at the year 2023 which is 315 hours compared to the year 2022 (43.5 hours), this indicated that the probability chances of power reliability in the year 2022(0.74) is greater than the year 2023 (0.566).

Furthermore, Figure 6 presents the results of 100 simulation carried out for the Loss of energy expected of Mando-Shiroro 330 kV Transmission network. It can be observed from Figure 6 that the normal distribution shows almost the same pattern for the year 2022 and 2023 respectively. The average Loss of energy expected (LOEE) 498.29 and 499.113 MW verified for the year 2022 and 2023. Which is very high compared to the international standard of less than 5.0 hours (Kumar *et al.,* 2024). The loss of load expected for the simulated data indicated the average of 562.25 and 844.90 MW/year for the year 2022 and 2023 respectively.

3.1.2. Reliability Evaluation Indices Output of MATLAB simulation for year 2022 and 2023

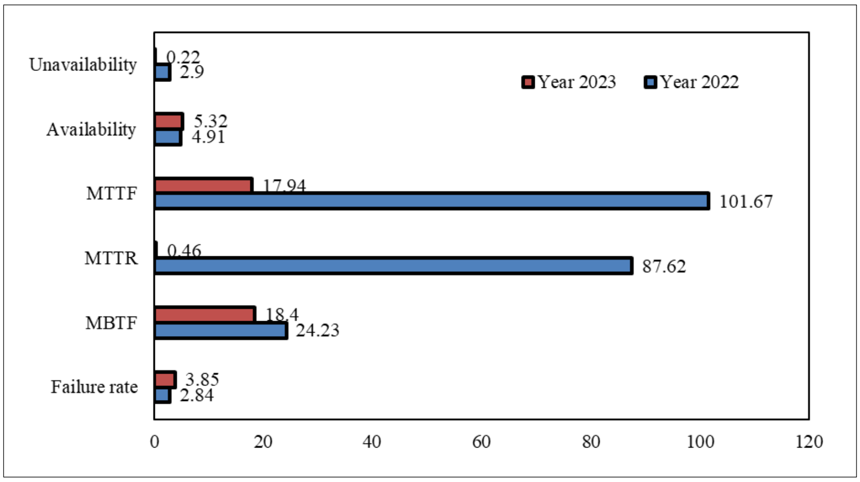

Figure 1 Results of reliability evaluation year 2022 and 2023

The output simulation findings for the 330kV Mando-Shiroro transmission network are shown in Figure 7. These indices include failure rate, Mean Time Before Failure (MTBF), Mean Time To Repair (MTTR), Mean Time To Failure (MTTF), availability, and unviability respectively.

The comparison findings from the MATLAB simulation for the reliability assessment of the Mando-Shiroro 330KV transmission network for the years 2022 and 2023 are displayed in Figure 7. Failure rates for the years 2022 and 2023 are 2.84 and 3.85, respectively, which means that the year 2023 will have a 1.01 higher failure rate than the year 2022. The years 2023 and 2022 had the highest availability and unavailability records, respectively, at 4.91 and 5.32. The year 2022 had the highest unavailability record, at 2.9, compared to 2023's 0.22. The unavailable results for 2022 are like the findings of [13] Additionally, the MBTF, MTTR, and MTTF results for the years 2022 and 2023 were 24.23, 87.62, and 101.67, 18.4, 0.46, and 17.94, respectively. The results of this study for MTTR and MBTF are extremely like those of Chen, et al. [14].

3.2. Comparative Analysis

Table 5 presents the results of comparative analysis of different model approaches on power transmission and reliability study. It can be observed from Table 5 that Markov-based model chain analysis suppresses all the models in terms of reliability as 98 %, while the Sequential Monte Carlo simulation procedure came in second with 91 % reliability, then Spatial and Weighted Least Squares have 78 and 68% respectively. This indicated that the Markov Model Based Reliability and Availability Analysis has the potential to solve the practical operation of the Mando-Shiroro power transmission network if carefully adopted.

Table 5 Comparative Analysis of Power Transmission system based on Different model Approach for System Reliability.

Source	Type of system	Type of model	Outcome of model	Overall system reliability (%)
Ahiakwo, et al. [15]	State estimation of the Nigerian 330KV transmission network using the Weighted Least Square optimization technique	Weighted Least Squares	The model was developed with 1.14% of maximum voltage error in comparison with state estimate result	68
Zhang, et al. [16]	Spatial-Temporal Reliability and Damage Assessment of Transmission Networks under Hurricanes	spatial-temporal reliability and damage assessment method	The model was able assess the spatial-temporal reliability with less 1.10 % error	78
Kothona, et al. [17]	Optimal demand response scheduling with real-time thermal ratings of overhead lines for improved network reliability	Sequential Monte Carlo simulation procedure	The model was able to Enhancement's reliability and economic metrics of the system with 5 %	91
Current study	Markov Model Based Reliability and Availability Analysis: A case Study of Mando-Shiroro 330kV Power Transmission Network	Markov Model Based system	Bus load A (100 MW) had the best operating reliability (0.980 base Markov base model analysis.	98

3.3. Roy Billinton Test 6 Bus System Performance Assessment

It can be observed from Figure 8 bus A, with 100MW capacity has the maximum reliability of 0.95 followed by bus E (40 MW) with a reliability of 0.93 and bus D which is (60MW) with the lowest reliability. However, this indicates that reliability depends on the effective repair time. Also;[18, 19] used the same bus capacity to run Roy Billinton Test 6 Bus System Performance Assessment. The results of the results obtained from bus capacity 100MW was similarly to results obtained from the work of [20].

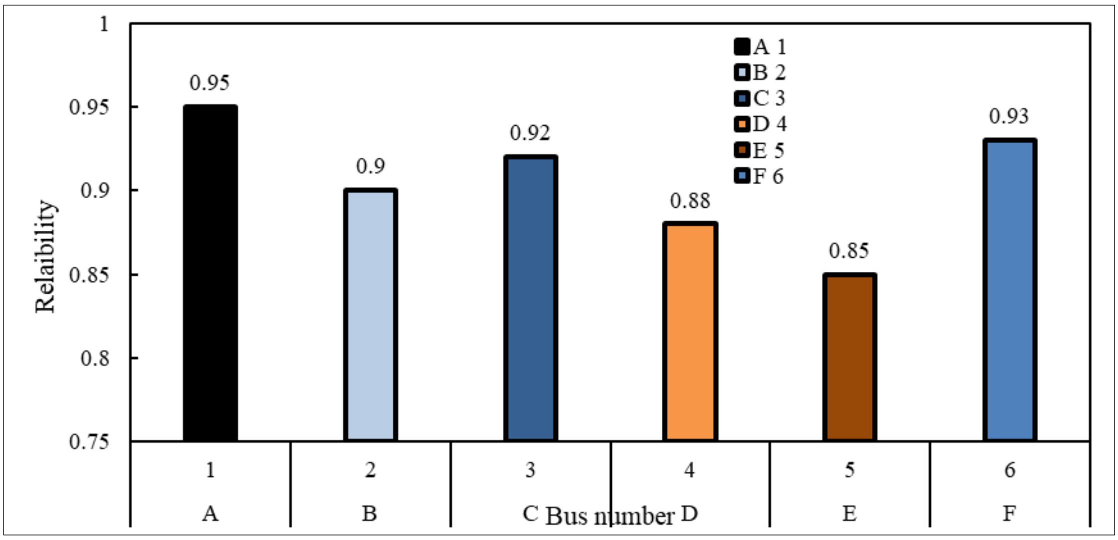

Figure 2 Reliability Indices results for Roy Billinton Test 6 Bus System Performance Assessment

Table 6 shows the results of simulation of indices obtained from Roy Billinton Test 6 Bus System Performance Assessment. It can notify from the Table the RBTS (Roy Billinton Test System) bus 6. Table 6 shows that the simulated Markov simulated optimized results will be dependable if used as a power transmission network. The expected energy not supplied (EENS) for the simulated Mando-Shiroro transmission network was 37.96 MW, which is above the bench with 3.96 MW and 35% difference. This can be linked to the station's enhanced ideal monthly frequency maintenance. Furthermore, the EENS and system dependability results were nearly identical to those of [22] research findings as 38.56 MW and 90.43% respectively.

Table 6 Results of simulation indices Roy Billinton test 6 bus system performance assessment compared to benchmark.

Roy Billinton Test 6 bus	Mando-Shiroro 330KV	Bench mark[21]	Shahbazian, et al. [22]
Average EENS (MW)	37.96	40	38.56

3.3.1. Roy Billinton Test System (RBTS) 6 Bus System simulation

The Table presents the results obtained from the MATLAB environment runs for the RBTS 6 bus system analysis. A benchmark for power system design and reliability studies is the Roy Billinton Test System. In particular, the 6-bus system functions as a condensed model that may be used to analyze the reliability of electrical power networks in various operational circumstances. Its numerous parts, which include buses, loads, transformers, and generators, can be used to model and assess system performance [20]. The system performance assessment was run on different scenarios such as components failure, load variation and maintenance schedule against the EENS and System reliability which are most significant tools in checking the quality and efficiency of a power transmission network. The simulation was carried out under the following parameters as follows:

3.3.2. Effect of components failure on EENS and system reliability

The outcomes of component failure are shown in Figure 9 together with the percentage of system dependability and the average predicted energy not provided. The Figure shows how component failure impacted both system dependability and EENS. The graph for system reliability remained nearly linear, but the EENS improved. A further rise in the percentage of components resulted in a sharp decline in both the EENS and system reliability, making the components failure from 10% to 30% manageable. Component failure poses a serious threat to the power transmission system network and has a substantial impact on the power system. According to Martyushev *et al.* (2023) components failure above 25 % led to increase in the EENS and decreases the system reliability.

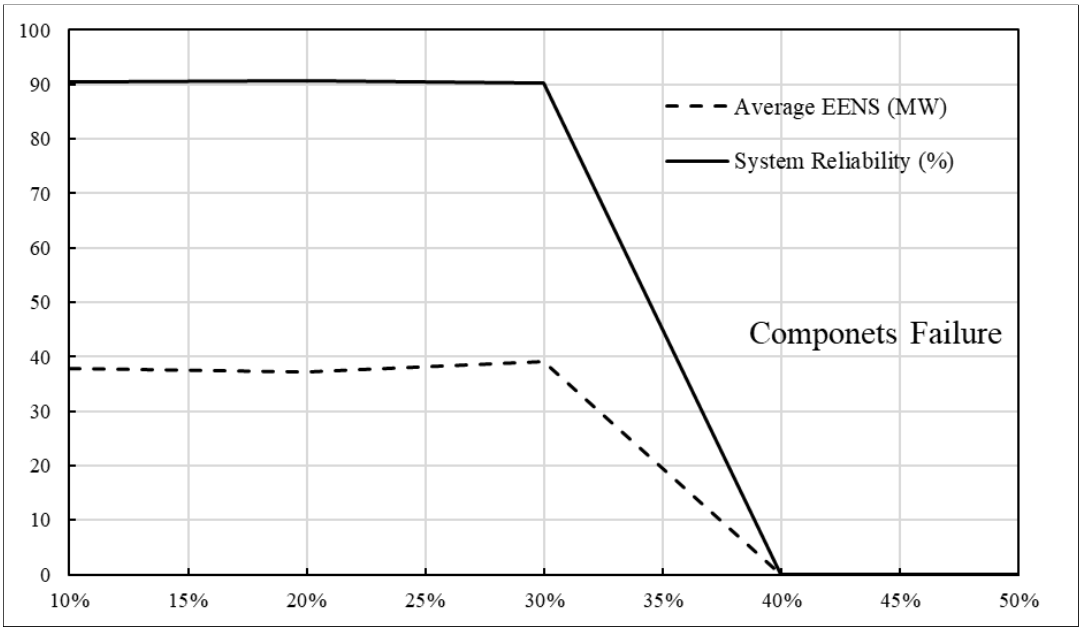

Figure 9 Effect of component failure on EENS and system reliability

3.3.3. Effect of load variation on EENS and system reliability

Figure 10 shows how the loading rate affects EENS and system reliability. Figure 9 demonstrated that the average expected system not supplied (AEENS) increased as the load rate increased, indicating that a larger load resulted in a more appropriate power supply. Nonetheless, Figure 10 shows that since the system's reliability remained nearly constant, increases in the loading rate resulted in a consistent power supply. The results of this study are consistent with those of Hou *et al.* (2023) who found that an increase in loading rate increased system reliability overall. Also, Kabir *et al.* (2023) in their work suggested that power loading rate led to lower system reliability.

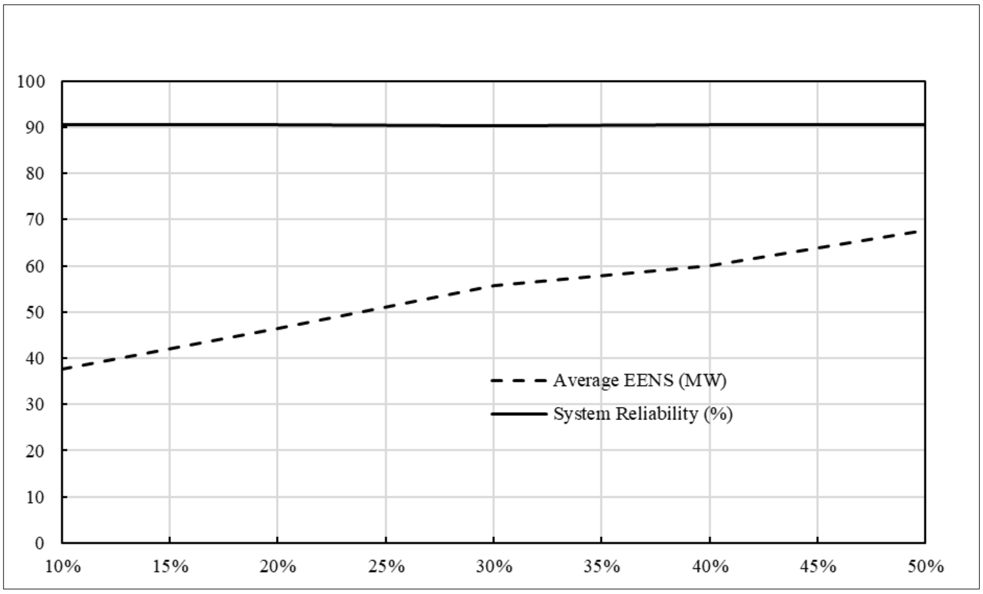

Figure 10 Effect of load variation on EENS and system reliability

3.3.4. Effect of maintenance schedule on EENS and system reliability

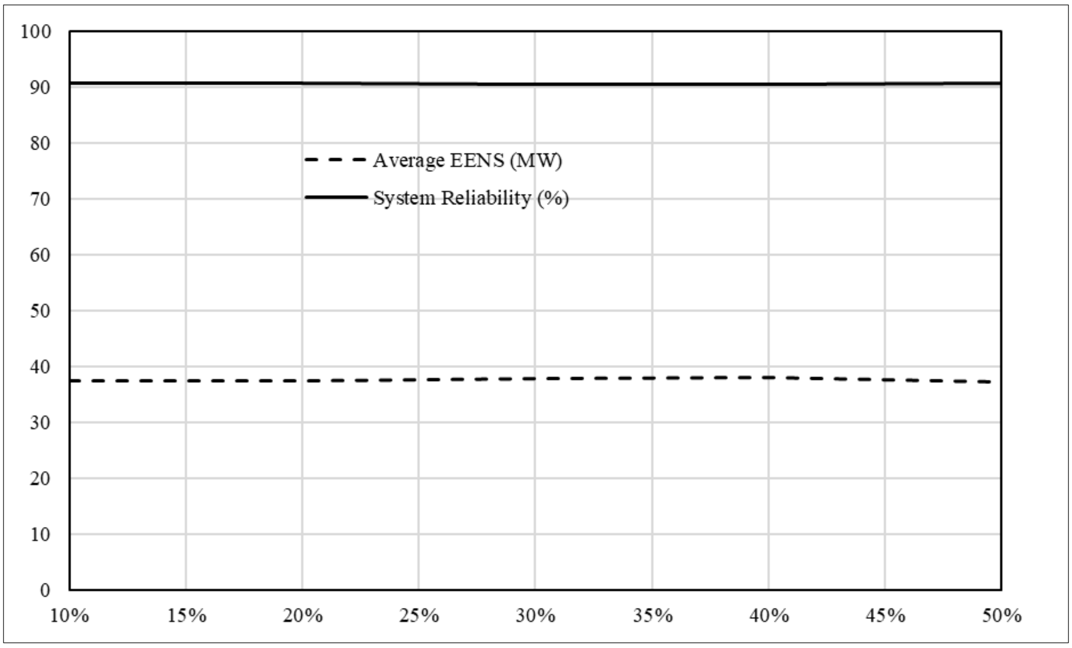

Figure 11 Effect of maintenance schedule on EENS and system reliability

Figure 11 shows the results of the maintenance schedule's effect on ENNS and system reliability, the figure shows that when the percentage of the maintenance schedule was increased from 10% to 20%, the average expected energy not supplied stayed constant at 37.47 MW. However, when the schedule maintenance was increased from 30% to 40%, the EENS decreased slightly from 40% to 50%, and the changes were made to 37.80 and 37.19 MW, respectively. Moreover, it also shows that the system reliability followed a similar pattern to the EENS against the percentage of schedule maintenance that changed from 10% to 20%. The system reliability value remained constant at 90%, then slightly decreased at 30% (90.51%), and then increased to 40% and 50% of schedule maintenance, resulting in values of 90.46 and 90.71, respectively. Overall findings showed that schedule maintenance raises EENS, which is bad for power transmission systems. The more the schedule maintenance, the higher the EENS. The results of this research work are in good agreement with the work of Mishra *et al.* (2024) on the influence of schedule maintenance on EENS and system reliability, more specifically that reduced schedule maintenance is more favorable to system reliability.

3.4. Practical Implication

Markov models as one of the influential tools in reliability and availability analysis for stochastic system behavior[23]. The Markov model played crucial roles in the analysis of power transmission network maintenance and stability efficiency on power grid, particularly for complex system lie the Mando-Shiroro 330kV transmission network, which serves as a crucial link in Nigeria's power infrastructure. They effectively account for constant failure and repair rate, enabling detailed assessment of system performance under various operational states. The practical implications of Markov Model base analysis are as follows:

3.4.1. Systematic prediction of system failure

Markov based models help engineers in predicting the like hood of system failure over time, it is done by modelling it failure and repair rate different components of the 330V power transmission network such as (Circuit breakers and transformer) to evaluate the system performance [24]. The rates of transmission between the failed and repaired states operational of the system can be quantified, established more visibility into potential vulnerabilities and failure hotspots in the network [25]. For example, a component with a high failure rate may need to be replaced or undergo more frequent maintenance to avoid unscheduled downtime.

3.4.2. Maintenance schedule optimization

Markov based models support optimal maintenance determination based on different components of the reliability network. For instance, preventing periodic maintenance via planned based predictive failure rate [26]. If a component is more likely to fail after a certain period, the Markov model can recommend replacing or maintaining it before a failure occurs. This helps in reducing the risk of unscheduled downtime, improving system availability, and ensuring that the network remains stable[27].

3.4.3. Systematic availability evaluation

Availability refers to the fraction of time the system is operational and can perform its intended function[28]. By modelling the various operational states and failure modes of the Mando-Shiroro 330kV network, Markov models allow engineers to calculate the system's availability. This can be used to determine how much time the system is expected to be down for repairs or maintenance and help in assessing whether the network meets the required availability standards. If the system's availability is found to be lower than required, modifications can be made to improve it, such as upgrading certain components or enhancing repair processes[29].

3.4.4. Enhance network resilience

By utilizing the Markov model for ongoing analysis, the Mando-Shiroro 330kV network can be designed to become more resilient to unexpected disruptions. Markov models can simulate the behavior of the network under various failure scenarios, helping to design more robust systems and backup mechanisms (e.g., redundant lines or spare parts). This enhances the overall resilience of the power transmission network, ensuring that the grid can recover more quickly from disturbances[30].

3.4.5. Decision support and risk management

Markov models allow for a quantifiable assessment of the risks associated with different components of the transmission network[31]. By providing a clear view of failure rates, repair times, and system reliability, operators can make informed decisions about resource allocation, risk mitigation strategies, and system upgrades. This data-driven decision-making helps prioritize investments in infrastructure and minimizes the likelihood of catastrophic failures that could result in large-scale blackouts or power losses[32].

4. Conclusion

This study highlights the critical role of reliability evaluation in the energy transmission sector, especially through the application of Markov Chain analyses to the Mando-Shiroro 330kV Transmission network. The findings show appreciable improvement in operational efficiency and reliability matrices, with 2022 recording the lowest power outages and highest operational hours. These results highlight the necessity for modern evaluation techniques such as Roy Billinton Test 6 Bus System Performance Assessment to replace traditional methods of the System Performance Assessment as revealed from The RBTS bus's simulation results showed an average EENS of 37.96 MW, with a matching system reliability of 90.54% respectively. However, adopting the Markov Model Based Reliability and Availability Analysis in practical operation of the Mando-Shiroro power network will enhance the reliability of power supply, while the Roy Billinton Test System (RBTS) 6 Bus System simulation will solve the problem of component failure, maintenance schedule and load variation in system reliability.

The application of Markov model-based reliability and availability analysis provides significant practical applications for power transmission networks like the Mando-Shiroro 330kV system. By predicting failures, optimizing maintenance, identifying critical components, and improving decision-making, operators can enhance the system's reliability, availability, and overall resilience.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

Author contributions

Conceptualization: M. M. Biu and A. E. Airoboman. Methodology and software: M. M. Biu. validation: M. M. Biu and A. E. Airoboman. formal Analysis: M. M. Biu. Investigation: F. O. Adunola and A. E. Airoboman. writing original draft preparation: M. M. Biu. review and editing: M. M. Biu and A. E. Airoboman The final manuscript was read and approved by both authors.

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