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RESEARCH PAPER

Optimizing Preventive Maintenance Intervals of Gas Turbine Generator Through a Reliability-Centered Analysis Approach

ABSTRACT

Gas Turbine Generators (GTGs) are critical assets that play a key role in ensuring the continuity of power generation in the oil and gas industry. The high frequency of failures in several GTG components during the 2021-2025 period has led to increased downtime and reduced system performance. This study aims to identify critical components, assess failure risks, and determine optimal preventive maintenance (PM) intervals using the Failure Mode and Effects Analysis (FMEA) and Reliability-Centered Maintenance (RCM) approaches. Actual GTG failure and maintenance data collected over a five-year period were used to support the analysis and validate the reliability-based PM optimization model. The FMEA results identified three critical components with the highest Risk Priority Numbers (RPNs): the Control System (320), Turbine (280), and Combustor (240). Reliability analysis was performed by evaluating the Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), availability, and reliability based on the Weibull distribution. The optimal PM intervals for individual components were determined to be 767 hours for the Control System, 662 hours for the Turbine, and 663 hours for the Combustor. Using a group maintenance strategy, these intervals were standardized to a common interval of 600 hours. The implementation of the 600-hour PM interval increased component reliability to 81.36%, 88.94%, and 71.23% for the Control System, Turbine, and Combustor, respectively, outperforming the existing 4,000-hour maintenance interval. These findings demonstrate that the proposed maintenance strategy can enhance system reliability while supporting operational continuity and production sustainability.

KEYWORDS: *Gas Turbine Generator, FMEA, RCM, Reliability, Preventive Maintenance*

1. Introduction

The oil and gas industry is a strategic sector that contributes significantly to Indonesia's economic development and energy security. Through exploration, production, and distribution activities, the industry supplies essential energy resources to various sectors, including manufacturing, transportation, and residential consumption [1]. Furthermore, the sector generates substantial government revenue through taxation, exports, and investments. Therefore, maintaining operational continuity and efficiency is crucial for ensuring a stable energy supply and supporting sustainable economic growth [2].

PT XYZ, located in East Java, Indonesia, is one of the country's major oil and gas producers, contributing approximately 25% of national crude oil production. To support production activities, the company operates continuously and relies on a Gas Turbine Generator (GTG) system as the primary source of electrical power for production equipment and auxiliary facilities [3]. Consequently, the reliability and performance of the GTG system are critical to maintaining operational continuity and production efficiency [4]. As a critical asset, failure of the GTG system can lead to partial or complete production shutdowns. Historical maintenance records from 2021 to 2025 indicate recurring GTG failures that resulted in substantial downtime and reduced operational performance [5].

Maintenance data show that the GTG system experienced an average of 29 failure events per year during the 2021-2025 period, resulting in approximately 338 h of downtime annually. Assuming a production loss of 5,000 barrels of oil per hour during power generation interruptions, the estimated annual production loss could reach 1.69 million barrels. These figures highlight the importance of improving GTG reliability to minimize production losses and ensure business continuity [6].

Preliminary investigations revealed that several failures occurred before the next scheduled preventive

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maintenance (PM) activity. This finding suggests that the current time-based maintenance policy is not fully aligned with the actual failure characteristics of the equipment. Existing PM intervals are primarily determined based on manufacturer recommendations and fixed maintenance schedules, with limited consideration of operating conditions and historical failure data [7]. Consequently, a reliability-based maintenance strategy is required to improve equipment performance and reduce unplanned downtime.

In modern asset management, maintenance optimization increasingly relies on quantitative indicators such as reliability, availability, and maintainability to enhance equipment performance and resource utilization [8]. Reliability-Centered Maintenance (RCM) provides a structured framework for identifying system functions, failure modes, and failure consequences, thereby supporting the development of maintenance policies based on operational requirements and equipment condition [9]. In addition, reliability metrics such as Mean Time Between Failures (MTBF), Mean Time To Repair (MTTR), availability, and reliability can be used to quantitatively evaluate equipment performance and determine appropriate maintenance intervals. Failure Mode and Effects Analysis (FMEA) complements this approach by systematically identifying and prioritizing failure modes according to their associated risks [10]. The integration of FMEA and RCM therefore enables the development of a data-driven maintenance strategy capable of reducing unplanned downtime and improving the overall reliability performance of the GTG [11].

Although previous studies have applied RCM and Weibull-based reliability analysis to determine optimal PM intervals, most have focused on individual components. However, limited attention has been devoted to integrating failure risk assessment, reliability evaluation, and maintenance interval harmonization for multiple critical components within a single operating system. In continuously operating GTG systems, maintenance decisions must consider not only component-level optimization but also the coordination of maintenance activities at the system level. Consequently, a research gap remains in integrating failure risk assessment, reliability characterization, individual PM optimization, and system-level maintenance decision-making within a unified framework.

To address this gap, this study proposes an integrated methodology combining FMEA, RCM, probability distribution analysis, and Weibull reliability modelling for preventive maintenance optimization in GTG systems. The proposed approach was developed and validated using actual failure and maintenance data collected between 2021 and 2025, representing real operating conditions in a continuously operating power generation system. The analysis identified the Control System, Turbine, and Combustor as the most critical components. The optimal PM intervals obtained for these components were 767 h, 662 h, and 663 h, respectively. Subsequently, alternative maintenance scenarios were evaluated to establish a unified system-level maintenance interval through a group maintenance approach.

The primary contribution of this study is the development of a reliability-based preventive maintenance optimization framework, validated using actual GTG failure and maintenance data collected over a five-year period (2021-2025). This approach integrates failure risk assessment, reliability analysis, maintenance interval optimization, and group maintenance decision-making within a unified framework for continuously operating GTG systems. Based on the evaluated scenarios, a unified maintenance interval of 600 h was selected as the most suitable maintenance policy. Under the proposed 600-h maintenance interval, the reliability of the Control System, Turbine, and Combustor increased to 81.36%, 88.94%, and 71.23%, respectively, compared with 22.39%, 15.79%, and 42.34% under the existing 4,000-h maintenance interval.

Therefore, this study extends the application of FMEA, RCM, and Weibull analysis beyond component-level optimization by introducing a data-driven framework that integrates risk prioritization, failure characterization, reliability assessment, maintenance interval scenario evaluation, and group maintenance scheduling. The proposed framework provides a practical and transferable approach for improving maintenance decision-making, reliability performance, and operational continuity in continuously operating GTG systems.

2. Experimental Procedure

The study employed a systematic methodology to develop a reliability-based maintenance strategy for the GTG system. A Functional Block Diagram (FBD) was first constructed to represent the system architecture and interactions among components. Subsequently, Pareto analysis was performed to identify critical components based on historical failure frequency.

The identified critical components were then evaluated using Failure Mode and Effects Analysis (FMEA) to assess failure risks through the calculation of Risk Priority Numbers (RPNs). Components with the highest risk levels were selected for further reliability assessment.

A Reliability-Centered Maintenance (RCM) approach was applied by analyzing failure and repair data through probability distribution fitting and estimating key reliability indicators, including MTBF, MTTR, availability, and reliability [12]. The resulting reliability characteristics were used to determine the optimal PM intervals for the critical components [13].

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Finally, maintenance interval optimization was conducted by evaluating alternative PM scenarios and implementing a group maintenance approach to synchronize maintenance activities at the system level. The selected maintenance policy was proposed to improve GTG reliability, reduce unplanned downtime, and enhance operational performance [14].

2.1 Functional Block Diagram (FBD)

A Functional Block Diagram (FBD) was developed to represent the functional architecture of the GTG system and the interactions among its major subsystems [15]. The FBD was used to identify functional dependencies and critical pathways affecting system performance and reliability. The resulting model provided the basis for critical component identification and subsequent reliability analyses.

2.2 Pareto Analysis

Pareto analysis was conducted using historical failure data to identify the components that contributed most significantly to GTG system failures [16]. Components were ranked according to failure frequency, downtime contribution, and operational impact [17]. The identified critical components were subsequently selected for FMEA, reliability analysis, and preventive maintenance optimization.

2.3 Failure Mode and Effects Analysis (FMEA)

Failure Mode and Effects Analysis (FMEA) was applied to assess the risks associated with potential failure modes of the critical components [18]. The analysis evaluated Severity (S), Occurrence (O), and Detection (D) ratings to calculate the Risk Priority Number (RPN) [19]:

$$RPN = \mathrm{S} \times \mathrm{O} \times \mathrm{D} \quad (1)$$

where S, O, and D represent the severity, occurrence, and detection ratings, respectively [20].

Failure modes with higher RPN values were assigned as a higher maintenance priority. The resulting risk rankings were used to support component prioritization and subsequent reliability-centered maintenance analysis [21] [22].

Tab.1. Indicator of Severity

General Criteria for Severity of FMEA	Evaluation S
Extremely serious failure It gives impact to compliance and or safety towards legal policy, with no previous warning	10
Extremely serious failure It gives impact to compliance and or safety towards legal policy, with previous warning	9
Serious failure It leads to primary function failure	8
Severe failure Restriction of system functional capability	7
Medium failure Restriction of system functional capability caused by failure of important aspect	6
Medium failure Restriction of system functional capability caused by failure of functional impairment	5
Medium failure System minor impairment in visual aspect.	4
Insignificant failure There is inconvenience of workers lead to slight impairment	3
Very minor failure Unlikely occurred that the failure would affect the system behavior.	2
No effect No consequences occurred because of system slight impairment	1

Tab.2. Indicator of Occurrence

General Criteria for Occurrence of FMEA	Evaluation O
Very high Failure occurred frequently	10
	9
High Repeated failure occurred	8
	7
Moderate Occasional occurrence of failure	6
	5
	4
Low Low occurrence of failure Unlikely detection, unless with significant effort	3

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Very low very low occurrence of failure	2
Unlikely Excluded failure mode, as it is unlikely occurred Still need preventive action	1

Tab.3. Indicator of Detection

Evaluation Criteria for Detection of FMEA	Evaluation D
Unlikely No proven failure, the detection unlikely find malfunction	10
	9
Low The malfunction has low detection probability	8
	7
Moderate The malfunction has moderate detection probability	6
	5
	4
High The malfunction has high probability of detection with proven methods for verification	3
	2
Certain The malfunction has very high detection probability with effective detection methods.	1

2.4 Probability Distribution Analysis of TTR and TTF

Reliability-Centered Maintenance (RCM) analysis was performed to assess component reliability and maintenance effectiveness using historical failure and repair data [23]. As a preliminary step, the statistical characteristics of component Time to Failure (TTF) and Time to Repair (TTR) were analyzed to identify the probability distributions that best represented the observed data [24].

The distribution fitting process was conducted using a goodness-of-fit analysis in Minitab 16. Several candidate distributions were evaluated, and the distribution with the best statistical fit was selected for each dataset [25] [26]. The selected models provided the distribution parameters required for reliability modelling, including the shape parameter (β) and scale parameter (η) in the case of the Weibull distribution [27].

The identified probability distributions were subsequently used to characterize component failure and repair behaviour and to support the estimation of reliability metrics. Accurate distribution fitting is essential because it directly affects the reliability assessment results and the determination of optimal preventive maintenance intervals. Therefore, this stage provides a statistical foundation for the subsequent reliability analysis and maintenance optimization process.

2.5 MTTR and MTBF Calculation

The calculation of Mean Time To Repair (MTTR) and Mean Time Between Failures (MTBF) was performed to characterize the repairability and operational reliability of the identified critical components [28]. MTBF represents the average operating time of a component before a failure occurs, whereas MTTR represents the average time required to restore a failed component to its operational condition [29]. These parameters were subsequently used to evaluate the reliability, maintainability, and availability of the critical components.

Prior to reliability assessment, the Time to Failure (TTF) and Time to Repair (TTR) datasets were analyzed to determine the probability distributions that best represented the observed failure and repair behaviour. In this study, the Weibull distribution was selected to model both failure and repair characteristics because of its flexibility in representing various failure patterns through the shape parameter (β) and scale parameter (η). The distribution parameters were estimated using the Least Squares Estimation (LSE) approach, specifically the Least Squares Estimation based on X and Y (LSXY) method, as implemented in Minitab 16.

For a given operating time, the parameter β represents the shape parameter that characterizes the failure rate behaviour, while η represents the scale parameter associated with the characteristic life or time scale of the component. The estimated values of β and η were subsequently used to evaluate component reliability at different operating intervals.

The selection of the probability distribution was based on a goodness-of-fit assessment using the correlation coefficient and the Anderson-Darling (AD) statistic. The correlation coefficient measures the degree of agreement

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between the observed data and the theoretical distribution, with values closer to one indicating a better fit. Meanwhile, the Anderson-Darling statistic evaluates the deviation between the empirical and theoretical distributions, placing greater emphasis on discrepancies in the distribution tails. A smaller AD value indicates a better representation of the observed data by the selected distribution model.

Once the appropriate probability distribution had been identified, the MTBF and MTTR values were calculated using the corresponding distribution parameters. These reliability metrics provided the basis for evaluating component performance and served as key inputs for the subsequent determination of reliability, availability, and preventive maintenance intervals.

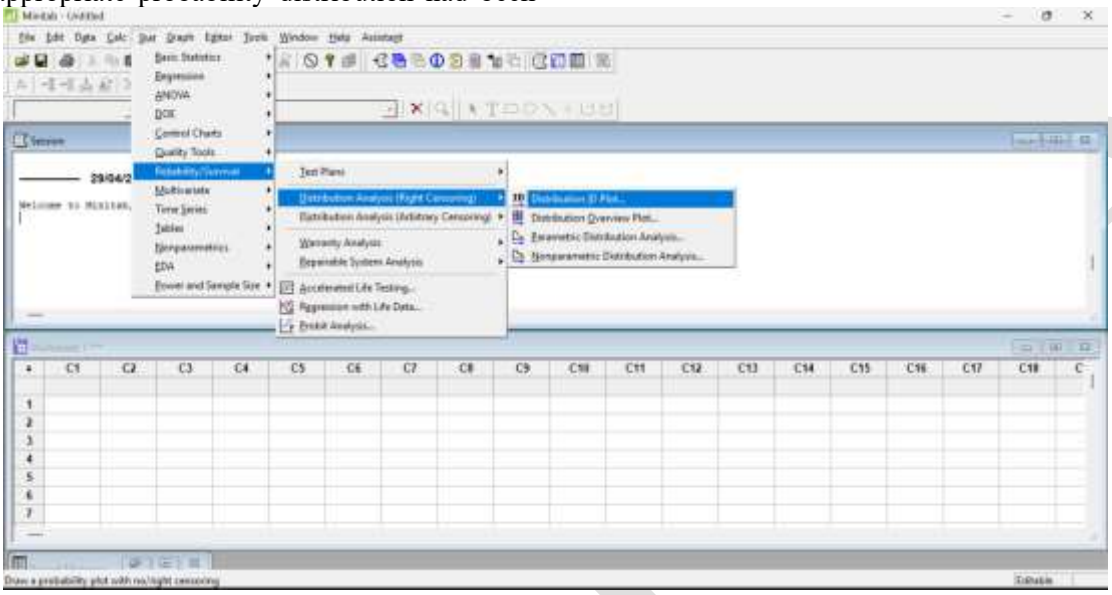


Fig.1. Reliability Analysis Using Minitab 16

2.6 Availability and Reliability Analysis

Availability and reliability analyses were conducted to evaluate the operational performance of the critical GTG components. Availability represents the ability of a component to remain operational when required, whereas reliability describes the probability of performing the intended function without failure over a specified operating period [30]. These indicators were used to assess the effectiveness of the existing maintenance policy and to support the determination of optimal preventive maintenance (PM) intervals [31].

Availability was calculated as follows [32]:

$$Availability = \frac{MTBF}{(MTBF + MTTR)} \quad (2)$$

where:

MTBF = Mean Time Between Failures (h)

MTTR = Mean Time To Repair (h)

Meanwhile, the reliability function for the Weibull distribution is expressed as follows [33]:

$$R(t) = e^{-(t/\eta)^{\beta}} \quad (3)$$

where:

$R(t)$ = reliability at operating time t

t = operating time (h)

β = shape parameter

η = scale parameter (characteristic life)

The resulting availability and reliability values were subsequently used to compare alternative maintenance scenarios and evaluate their impact on the overall performance of the GTG system.

2.7 Preventive Maintenance Interval Determination

Preventive maintenance (PM) intervals were determined based on the reliability characteristics of the critical components. The objective was to identify maintenance intervals that minimize failure risk while ensuring efficient maintenance execution [7].

The PM interval calculation was performed using the following procedure:

1. Determine the average operating hours per month (t).
2. Calculate the number of failures occurring during the observation period (k).
3. Calculate the average repair time per month (μ).
4. Determine the average inspection time (i).
5. Calculate the inspection frequency (n).
6. Determine the inspection interval (ti).

The optimal component-level PM intervals obtained from this analysis were subsequently used as inputs for maintenance interval scenario evaluation and group maintenance scheduling. This approach enabled the development of an integrated maintenance policy that balances reliability improvement, operational continuity, and maintenance efficiency.

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2.8 Proposed PM Optimization Model

The final stage of the study involved the development of a preventive maintenance (PM) optimization model based on the reliability analysis results and the optimal PM intervals determined in the previous stages. The proposed model was designed to support maintenance decision-making and improve the reliability performance of the GTG system.

A group maintenance approach was adopted to synchronize the maintenance schedules of multiple critical components. This approach enables maintenance activities to be performed in a coordinated manner, thereby improving maintenance efficiency in terms of resource utilization, maintenance execution time, and downtime reduction [34]. By aligning maintenance activities within a common maintenance interval, operational disruptions can be minimized while ensuring that critical components receive maintenance at appropriate intervals.

The proposed maintenance policy was evaluated using the reliability results obtained for the critical components under different maintenance interval scenarios. The selected group maintenance interval was subsequently recommended as the optimal maintenance strategy for the GTG system. The implementation of this strategy is expected to improve system reliability, reduce failure frequency, minimize unplanned downtime, and support continuous operational performance [6].

3. Result & Discussion

3.1 Historical Failure Data of GTG Components

The GTG system was selected as the case study because it serves as the primary power generation unit supporting production and auxiliary operations at PT XYZ. Given the continuous operating conditions of approximately 720 h per month, the reliability of the GTG system is critical to maintaining production continuity and minimizing operational disruptions.

Historical failure and maintenance records from 2021 to 2025 were collected and analyzed to characterize component failure behavior and assess system reliability [35]. These data provided the basis for critical component identification, failure risk assessment, reliability evaluation, and preventive maintenance optimization.

The historical failure data used in this study are presented in the following section.

Tab.4. Historical Failure Data of GTG Components

Main Components	Actual Start Date	Actual Start Time	Actual Finish Date	Actual Finish Time
Control System	09/01/2021	03:11:27	09/01/2021	09:24:03
Control System	14/01/2021	05:45:56	14/01/2021	19:58:20
Compressor	16/01/2021	08:57:34	19/01/2021	09:23:28
Combustor	23/01/2021	03:21:01	25/01/2021	10:12:45
Combustor	26/05/2021	08:27:18	30/05/2021	05:41:02
Combustor	31/05/2021	08:01:00	01/06/2021	13:55:48
Control System	01/06/2021	10:04:55	01/06/2021	13:12:07
Control System	28/07/2021	07:36:21	29/07/2021	04:55:45
Control System	23/08/2021	06:00:00	23/08/2021	11:18:36
Air Inlet Filter	28/08/2021	06:24:00	01/09/2021	01:20:10
Power Conditioning	03/12/2021	06:00:00	05/12/2021	03:39:29
Turbine	17/02/2022	03:39:29	17/02/2022	15:58:53
Control System	17/02/2022	00:44:55	17/02/2022	08:39:07
Combustor	28/03/2022	01:57:51	29/03/2022	09:44:37
Turbine	24/07/2022	15:31:15	29/07/2022	13:52:27
Turbine	08/09/2022	11:11:50	09/09/2022	18:24:26
Turbine	25/12/2022	06:58:07	27/12/2022	01:07:43
Turbine	23/02/2023	03:21:14	26/02/2023	08:02:26
Control System	01/03/2023	01:03:48	02/03/2023	02:42:24
Control System	13/03/2023	15:00:06	14/03/2023	10:28:18
Turbine	13/04/2023	09:48:19	16/04/2023	01:24:07
Turbine	14/06/2023	06:14:39	16/06/2023	13:14:03
Air Inlet Filter	22/06/2023	00:14:25	04/07/2023	06:27:17
Turbine	29/06/2023	14:12:58	03/07/2023	12:56:10
Generator	03/08/2023	02:28:42	09/08/2023	09:48:19
Control System	14/09/2023	09:08:26	14/09/2023	16:55:14
Turbine	15/09/2023	07:17:52	19/09/2023	21:45:16
Control System	27/10/2023	15:10:00	29/10/2023	00:28:36
Control System	04/03/2024	08:42:12	05/03/2024	10:03:48
Power Conditioning	07/03/2024	08:49:27	10/03/2024	06:57:22

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Main Components	Actual Start Date	Actual Start Time	Actual Finish Date	Actual Finish Time
Compressor	07/03/2024	01:07:36	11/03/2024	08:06:54
Combustor	21/03/2024	08:06:54	27/03/2024	04:28:10
Generator	05/05/2024	07:19:50	10/05/2024	07:28:55
Air Inlet Filter	18/06/2024	06:00:00	19/06/2024	01:39:03
Power Conditioning	18/07/2024	07:28:55	21/07/2024	02:04:04
Combustor	25/09/2024	00:41:07	28/09/2024	12:19:53
Control System	28/09/2024	02:04:04	28/09/2024	15:41:16
Control System	14/11/2024	07:36:20	15/11/2024	09:49:32

3.2 Functional Block Diagram (FBD) of the GTG System

Historical failure records indicate that GTG failures are associated with multiple interrelated components operating within an integrated system. To facilitate system-level analysis, a Functional Block Diagram (FBD) was constructed to represent the functional architecture of the GTG system and the interactions among its major subsystems.

The FBD provides a structured representation of component functions, material and energy flow, and subsystem interdependencies [36]. Such a representation is essential for understanding how component failures may propagate through the system and affect overall operational performance. In addition, the FBD supports the identification of critical components and functional pathways that require further reliability and risk analysis.

The resulting FBD serves as the basis for the subsequent Pareto analysis, FMEA, and Reliability-Centered Maintenance (RCM) evaluation. The Functional Block Diagram of the GTG system is shown in Figure 2.

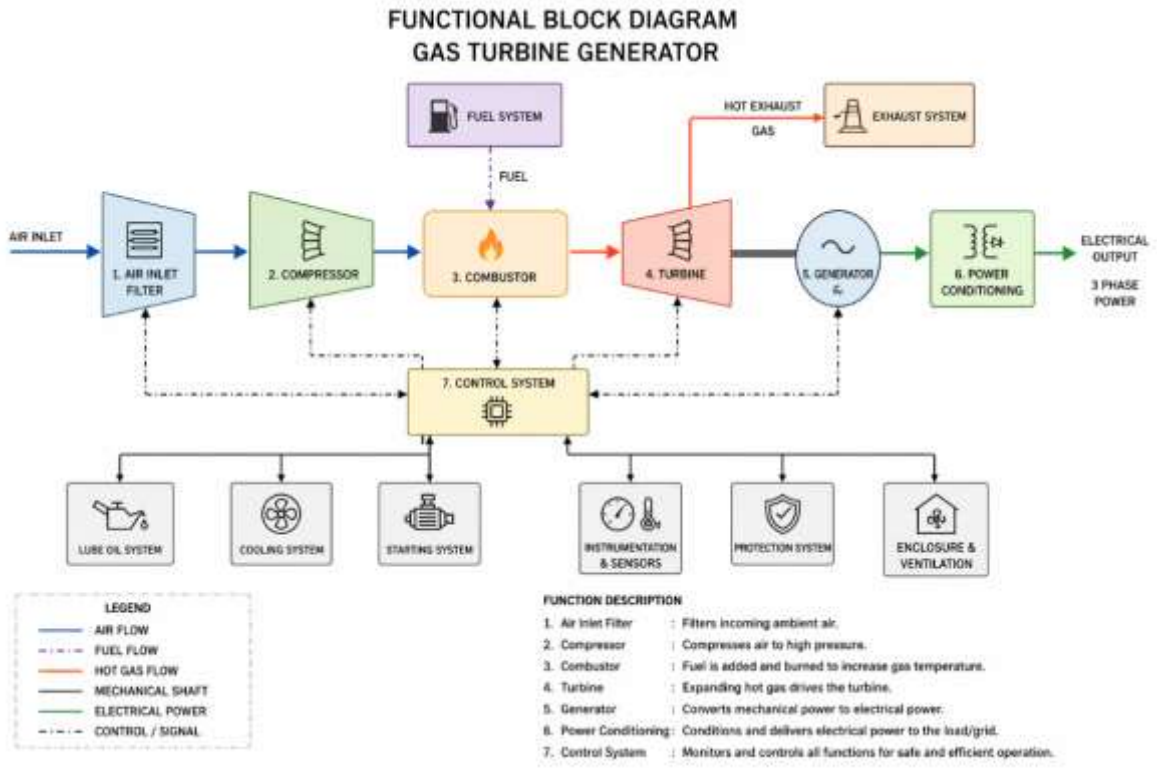


Fig.2. Functional Block Diagram (FBD) of the GTG System

Based on the Functional Block Diagram (FBD), the GTG system consists of seven major subsystems that collectively support the power generation process [3].

1. Air Inlet Filter

The power generation process begins with ambient air entering the system through the Air Inlet Filter. This subsystem removes dust, airborne particles, and other contaminants to ensure clean intake air and protect downstream equipment from premature degradation.

2. Compressor

The filtered air is compressed to increase its pressure and temperature before being supplied to the combustion chamber. The compressor plays a critical role in maintaining the thermodynamic efficiency of the gas

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turbine cycle.

3. Combustor (Combustion Chamber)

In the combustion chamber, compressed air is mixed with fuel and ignited to produce high-temperature and high-pressure combustion gases. These gases serve as the primary energy source for turbine operation.

4. Turbine

The combustion gases expand through the turbine stages, converting thermal energy into mechanical energy through the rotation of turbine blades and shaft assemblies.

5. Generator

Mechanical power generated by the turbine is transmitted to the generator, where it is converted into electrical energy to support production and auxiliary operations.

6. Power Conditioning System

The generated electrical power is processed by the power conditioning system to regulate voltage, frequency, and overall power quality before distribution to the electrical network and connected loads.

7. Control System

The control system supervises and regulates the operation of the GTG by monitoring key operating parameters, executing protection functions, and ensuring safe, stable, and efficient system performance.

The FBD provides a systematic representation of the functional architecture of the GTG system and the interactions among its major subsystems. Understanding these functional relationships is essential for evaluating failure propagation mechanisms and assessing their potential impact on overall system reliability.

3.3 Pareto Analysis

Historical maintenance records from 2021 to 2025 were analyzed to determine the failure frequency of each GTG component. Failure frequency was used as an initial screening criterion to quantify the contribution of individual components to overall system failures. Components with a high number of failure occurrences were considered more likely to influence system reliability and operational performance.

A Pareto analysis was subsequently performed to rank components according to their failure frequency and to identify the dominant contributors to GTG failures. This approach enabled the selection of critical components that accounted for the majority of failure events and therefore warranted further investigation.

The results of the Pareto analysis served as the basis for the subsequent FMEA and RCM analyses, ensuring that reliability assessment and maintenance optimization efforts were focused on the components with the greatest impact on system performance. The historical failure frequency data are presented below.

Tab.5. Failure Frequency of GTG Components

Component	Failure Frequency	Cumulative Failures	% Failure	% Cumulative Failures
Control System	17	17	36%	36%
Turbine	13	30	28%	64%
Combustor	7	37	15%	79%
Air Inlet Filter	3	40	6%	85%
Power Conditioning	3	43	6%	91%
Compressor	2	45	4%	96%
Generator	2	47	4%	100%

Historical failure data were analyzed using a Pareto Diagram to identify the components that contributed most significantly to GTG system failures. The analysis was based on component failure frequency and was used to prioritize components for further investigation. Consistent with the Pareto principle, failure occurrences were concentrated in a limited number of components, indicating that targeted maintenance actions on these components could provide the greatest improvement in system reliability and operational continuity [16].

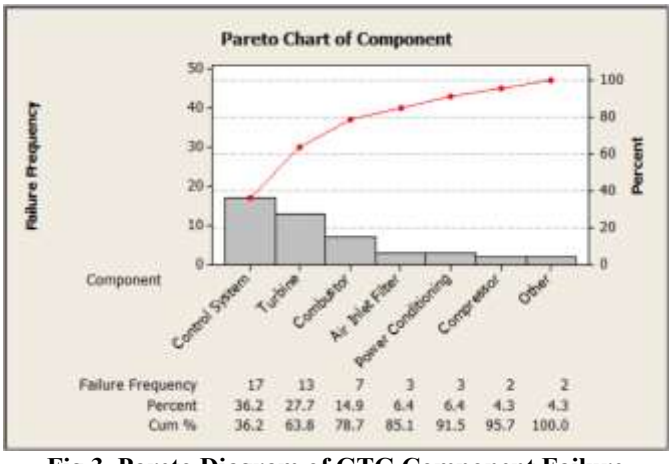


Fig.3. Pareto Diagram of GTG Component Failure

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Frequency

The Pareto analysis revealed that failure occurrences were highly concentrated in three components: the Control System (36.2%), Turbine (27.7%), and Combustor (14.9%). Together, these components accounted for approximately 80% of all GTG failures, indicating their dominant influence on system downtime and reliability performance.

This finding is consistent with the Pareto principle, which suggests that a relatively small number of causes are responsible for the majority of observed failures. Therefore, the Control System, Turbine, and Combustor were identified as the most critical components and prioritized for subsequent FMEA, reliability analysis, and preventive maintenance interval optimization. Targeting these components is expected to yield the most significant improvement in system reliability and operational continuity.

3.4 Failure Mode and Effects Analysis (FMEA)

The Pareto analysis identified the Control System, Turbine, and Combustor as the primary contributors to GTG system failures. To evaluate the risks associated with potential failure modes of these critical components, Failure Mode and Effects Analysis (FMEA) was performed. The analysis assessed the severity of failure consequences, the likelihood of occurrence, and the effectiveness of existing detection controls. These factors were used to calculate the Risk Priority Number (RPN) for each failure mode [37].

The calculated RPN values were subsequently used to rank failure modes according to their risk level and to identify areas requiring priority maintenance attention. Failure modes with higher RPN values were considered more critical due to their greater impact on system reliability and operational performance. The FMEA results also served as an input for the subsequent Reliability-Centered Maintenance (RCM) analysis and preventive maintenance interval optimization. The calculated RPN values are presented in Table 6.

Tab.6. Failure Mode and Effects Analysis (FMEA) and Risk Priority Number (RPN) Assessment

Equipment	Function	Dominant Failure Mode	Effect / Impact	S	O	D	RPN
Control System	Controls and monitors GTG system operations	Sensor/transmitter failure or control fault	Failure to accurately control operating parameters, potentially resulting in system trip	8	8	5	320
Turbine	Converts hot gas energy into mechanical energy	High vibration / blade damage	Mechanical damage and system shutdown	8	7	5	280
Combustor	Performs the combustion process of the air-fuel mixture	Flame instability / injector failure	Unstable combustion that may result in unit trip	8	6	5	240
Air Inlet Filter	Filters incoming air before entering the turbine system	Filter blockage / high differential pressure	Reduced airflow causing lower turbine performance and increased energy consumption	7	5	4	140
Power Conditioning	Stabilizes and regulates electrical power quality	Voltage fluctuation / module failure	Instability in electrical power supply	7	5	4	140
Compressor	Increases air pressure before the combustion process	Compressor fouling / overheating	Suboptimal air pressure and reduced system efficiency	6	4	5	120
Generator	Converts mechanical energy into electrical energy	Generator relay fault / overheating	Loss of electrical power and disruption of system operation	7	4	4	112

The FMEA results identified three components with the highest risk levels within the GTG system, namely the Control System, Turbine, and Combustor, with RPN values of 320, 280, and 240, respectively. Higher RPN values indicate a greater level of failure risk and therefore require higher priority in maintenance planning and risk mitigation efforts [19]. The RPN values were derived from the combined assessment of Severity (S), Occurrence (O), and Detection (D) for each identified failure mode [20].

Among all evaluated components, the Control System exhibited the highest RPN value (320). The dominant failure modes were associated with sensor/transmitter malfunctions and control system disturbances. Failures in the control system may lead to inaccurate regulation of GTG operating parameters, potentially resulting in

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system trips and unplanned shutdowns. The relatively high occurrence rating indicates that these failures occur frequently, while their operational consequences significantly affect the performance and continuity of GTG operation [38]. Consequently, the Control System was identified as the most critical component from a risk perspective.

The Turbine was ranked second, with an RPN value of 280. The dominant failure modes included excessive vibration and turbine blade damage, both of which can lead to severe mechanical failures and system shutdowns. As the primary component responsible for converting thermal energy into mechanical power, turbine failures directly affect the power generation process. The high RPN value therefore reflects the substantial impact of turbine-related failures on GTG reliability and availability.

The Combustor recorded an RPN value of 240, primarily due to flame instability and injector failures. These failure modes can disrupt the combustion process, reduce operating efficiency, and potentially trigger unit trips. In addition to affecting system performance, combustor failures may increase fuel consumption and result in abnormal operating conditions, thereby reducing overall system reliability.

The FMEA results demonstrate that failure risk within the GTG system is concentrated in a limited number of components. Therefore, the Control System, Turbine, and Combustor were selected for detailed reliability assessment, including probability distribution analysis, MTBF and MTTR estimation, and preventive maintenance interval optimization. This targeted approach ensures that maintenance improvements are focused on the components with the greatest influence on overall system reliability and operational continuity.

3.5 Probability Distribution Analysis of TTR and TTF

Following the identification of the critical components, probability distribution fitting was performed on the Time to Failure (TTF) and Time to Repair (TTR) data to characterize the failure and repair behaviour of the GTG components. Historical failure and maintenance records were analyzed using Minitab 16 to determine the statistical distribution that best represented the observed data [26].

Several candidate distributions were evaluated, and the most appropriate distribution for each dataset was selected based on the goodness-of-fit results. The selection criterion was the correlation coefficient, where higher values indicate a closer agreement between the observed data and the theoretical distribution model. The selected distributions and their corresponding parameters were subsequently used in the estimation of reliability-related metrics, including MTBF, MTTR, availability, and reliability.

The distribution fitting results provide the statistical basis for modelling component failure and repair characteristics and serve as key inputs for the subsequent reliability analysis and preventive maintenance interval optimization. The results of the probability distribution analysis for the critical GTG components are presented below.

Tab.7. Historical TTR and TTF Data for Critical GTG Components (2021-2025)

TTR (hour)			TTF (hour)		
Control System	Turbine	Combustor	Control System	Turbine	Combustor
6.21	12.32	52.86	116.37	3767.54	2902.24
14.21	118.35	93.23	3294.11	980.32	26.33
3.12	31.21	53.91	1362.4	2568.56	7196.03
21.32	42.16	31.78	601.07	1369.23	17398.37
5.31	76.69	116.35	4253.44	1105.76	4364.22
7.9	63.6	59.65	9040.41	1420.84	1363.95
25.64	55.99	85.6	276.29	312.98	
19.47	94.72		4390.67	1762.36	
7.78	110.46		1030.25	8595.85	
33.31	113.09		3040.23	2254.04	
25.36	91.59		4952	2663.13	
13.62	187.31		1119.92	2306.64	
26.22	103.74		1486.9		
26.6			1590.46		
55.48			1418.77		
21.73			2737.9		
4.39					

The probability distribution fitting was conducted using probability plot analysis with Least Squares XY (LSXY) estimation for complete datasets. The most appropriate distribution was selected based on the correlation

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coefficient, where the highest value indicated the best agreement between the observed and theoretical distributions. In addition, the visual alignment of data points with the probability plot reference line was considered to confirm the adequacy of the fit. The selected distributions were subsequently used to estimate the reliability parameters required for MTBF, MTTR, reliability, and preventive maintenance interval analyses [25].

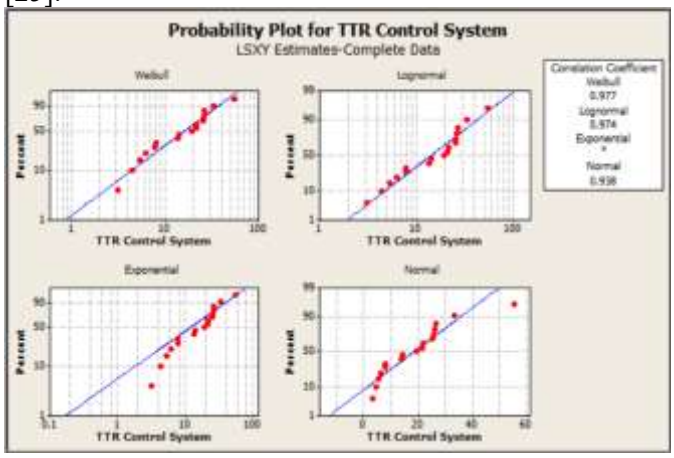


Fig.4. Probability Plot for TTR Control System

The probability distribution fitting results indicate that the Control System TTR data follow a Weibull distribution, with an Index of Fit of 0.977, the highest among all candidate distributions evaluated. This result demonstrates that the Weibull distribution provides the closest representation of the observed repair-time behavior. Therefore, the Weibull model was selected for subsequent calculations of reliability-related parameters, including MTTR, availability, and preventive maintenance intervals. The strong goodness-of-fit also suggests that the repair characteristics of the Control System can be reliably described using Weibull-based modeling.

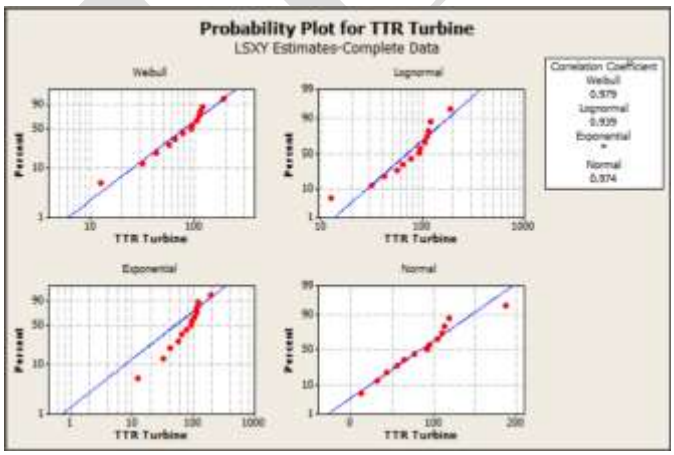


Fig.5. Probability Plot for TTR Turbine

Figure 5 shows that the Weibull distribution provides the best fit for the Turbine TTR data, with the highest correlation coefficient (0.979) among the evaluated distributions. The close alignment of the observed data points with the fitted reference line indicates that the Weibull model adequately captures the repair-time characteristics of the Turbine. Therefore, the Weibull distribution was selected for subsequent estimation of MTTR and maintainability-related parameters, providing a robust basis for the reliability and preventive maintenance analyses.

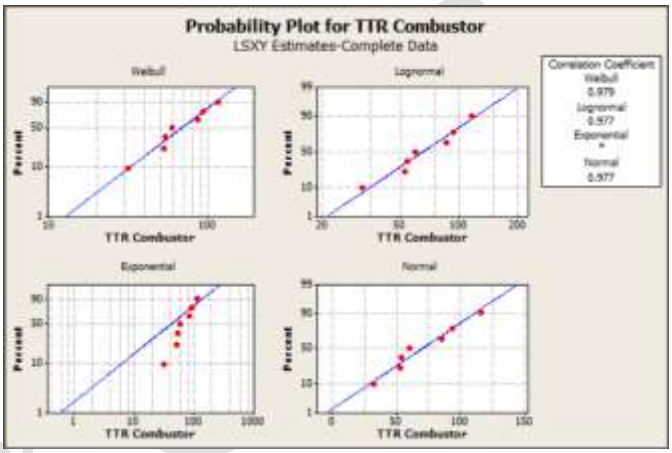


Fig.6. Probability Plot for TTR Combustor

The TTR data of the Combustor followed a Weibull distribution, yielding the highest Index of Fit value of 0.979 among the evaluated probability distributions. This finding confirms that the Weibull distribution provides the best representation of the observed repair-time data and is suitable for subsequent reliability analysis.

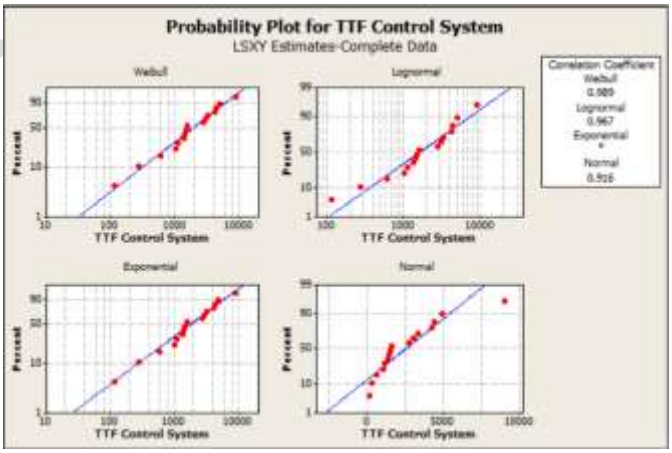


Fig.7. Probability Plot for TTF Control System

The Control System TTF data followed a Weibull distribution, yielding the highest Index of Fit value of 0.989 among the evaluated distributions. This finding indicates that the Weibull model provides the best representation of the observed failure-time behavior and

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was therefore selected for subsequent reliability analysis.

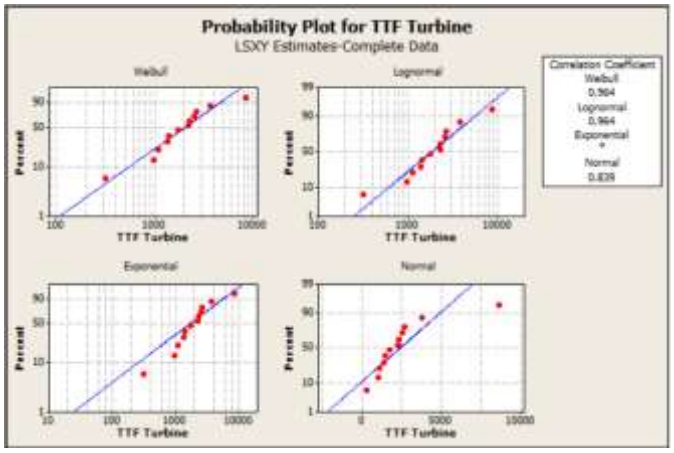


Fig.8. Probability Plot for TTF Turbine

Fig. 8 shows that the Weibull distribution provides the best fit for the Turbine TTF data, with the highest correlation coefficient (0.964) among the evaluated distributions. The close alignment of the observed data points with the fitted Weibull line indicates that the model adequately represents the failure-time characteristics of the Turbine. Consequently, the Weibull distribution was selected for estimating MTBF, reliability, and preventive maintenance intervals, providing a reliable basis for the subsequent maintenance optimization.

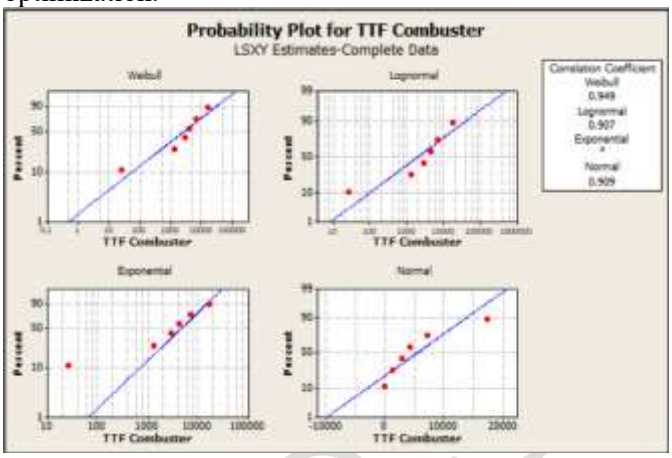


Fig.9. Probability Plot for TTF Combustor

The TTF data of the Combustor followed a Weibull distribution, yielding the highest Index of Fit value of 0.949 among the evaluated probability distributions. This result indicates that the Weibull model provides the best representation of the observed failure-time behavior and was therefore selected for subsequent reliability analysis. The summary of the probability distribution analysis is presented in Table 8.

Tab.8. Comparison of Correlation Coefficients for Candidate Probability Distributions

Parameter		Weibull	Lognormal	Exponential	Normal	Selected Distribution
TTR	Control System	0,977	0,974	*	0,938	Weibull
	Turbine	0,979	0,939	*	0,974	Weibull
	Combustor	0,979	0,977	*	0,977	Weibull
TTF	Control System	0,989	0,967	*	0,916	Weibull
	Turbine	0,964	0,964	*	0,839	Weibull
	Combustor	0,949	0,907	*	0,909	Weibull

3.6 MTTR and MTBF Analysis

Based on the TTR and TTF analyses performed using Minitab 16, the MTTR, MTBF, and Weibull parameters (β and η) were estimated for the identified critical components. These parameters provide quantitative insights into the reliability and failure characteristics of each component and serve as key inputs for reliability assessment and preventive maintenance optimization [39][40]. Variations in the estimated values reflect differences in component failure behavior and repair performance under actual operating conditions. The resulting MTTR, MTBF, β, and η values for the Control System, Turbine, and Combustor are presented below.

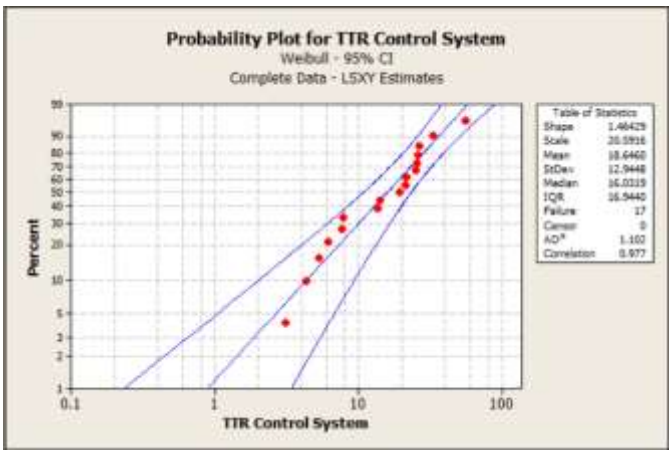


Fig.10. Parameter MTTR Control System

For the Control System, the Weibull analysis of the TTR data resulted in β = 1.46429 and η = 20.5916 h, with an AD statistic of 1.102 and a correlation coefficient of

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0.977, indicating a good fit of the Weibull model. The estimated MTTR was 18.6460 h, suggesting that restoration of the Control System requires approximately 18.65 h on average. The obtained β value greater than one indicates a non-random repair pattern and reflects the influence of failure complexity on repair duration. This result highlights the importance of improving maintenance efficiency to reduce downtime associated with Control System failures.

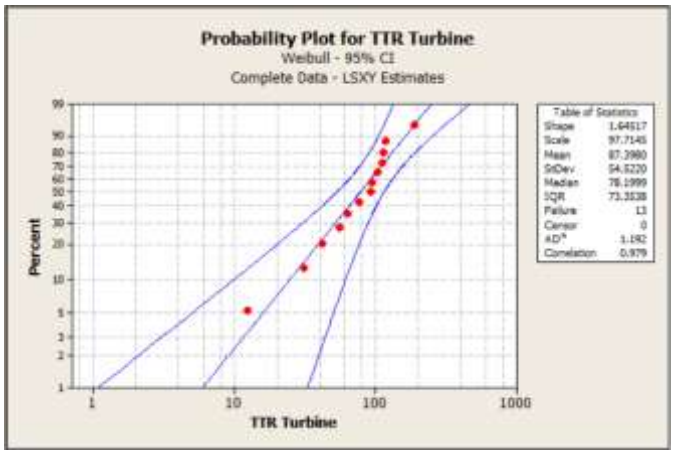


Fig.11. Parameter MTTR Turbine

For the Turbine, the Weibull analysis of the TTR data yielded a shape parameter (β) of 1.64517 and a scale parameter (η) of 97.7145 h. The goodness-of-fit results showed an Anderson-Darling (AD) statistic of 1.192 and a correlation coefficient of 0.979, indicating that the Weibull distribution adequately represents the observed repair-time data. Based on the estimated Weibull parameters, the MTTR was calculated as 87.3980 h.

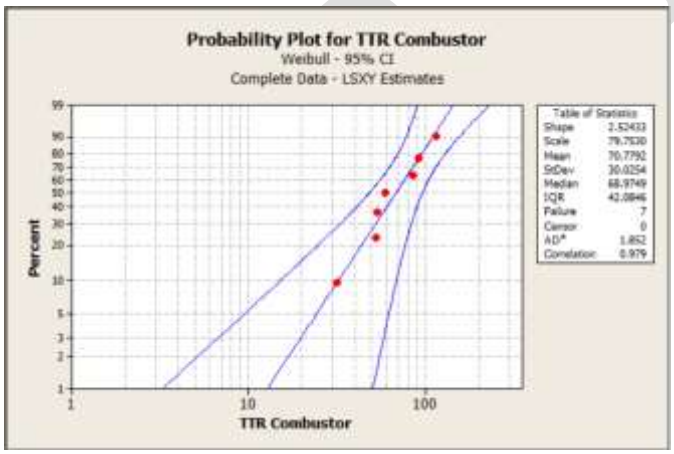


Fig.12. Parameter MTTR Combustor

For the Combustor, the Weibull analysis of the TTR data resulted in a shape parameter (β) of 2.52433 and a scale parameter (η) of 79.7530 h. The goodness-of-fit assessment yielded an Anderson-Darling (AD) statistic of 1.852 and a correlation coefficient of 0.979, indicating that the Weibull distribution adequately represents the observed repair-time data. Based on the estimated parameters, the MTTR was calculated as 70.7792 h.

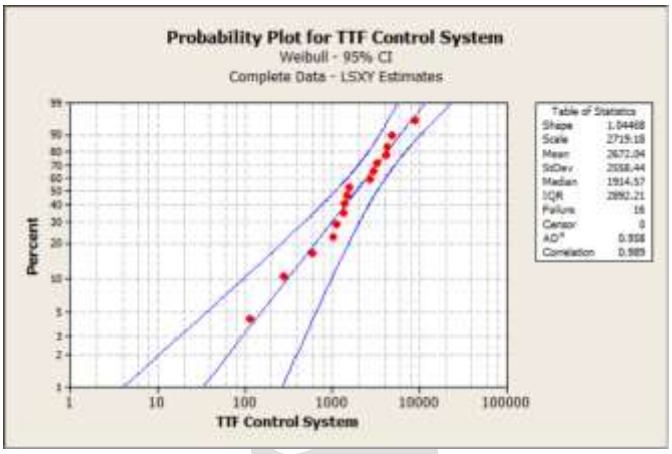


Fig.13. Parameter MTBF Control System

For the Control System, the Weibull analysis of the TTF data yielded a correlation coefficient of 0.989 and an Anderson-Darling (AD) statistic of 0.958, indicating an excellent fit between the observed failure-time data and the Weibull model. The estimated Weibull parameters were β = 1.04468 and η = 2719.18 h, resulting in an MTBF of 2672.04 h.

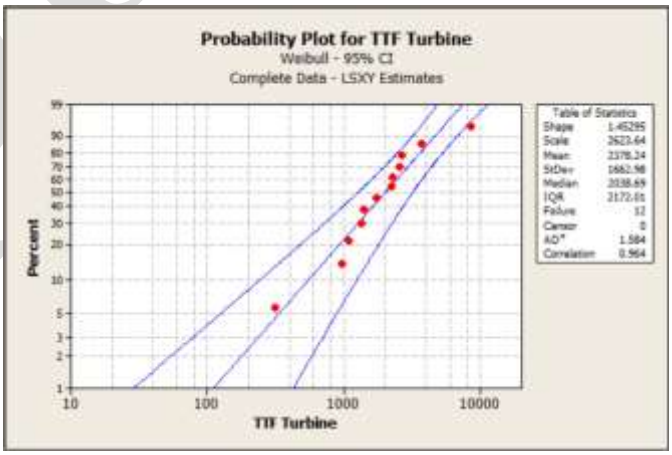


Fig.14. Parameter MTBF Turbine

For the Turbine, the Weibull analysis of the TTF data produced a correlation coefficient of 0.964 and an Anderson-Darling (AD) statistic of 1.584, indicating that the Weibull distribution adequately represents the observed failure-time data. The estimated Weibull parameters were β = 1.45295 and η = 2623.64 h, resulting in an MTBF of 2378.24 h.

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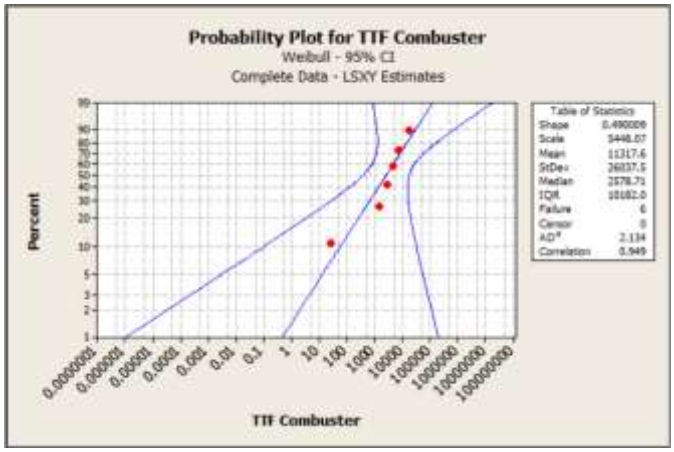


Fig.15. Parameter MTBF Combustor

For the Combustor, the Weibull analysis of the TTF data yielded a correlation coefficient of 0.949 and an Anderson-Darling (AD) statistic of 2.134, indicating an acceptable fit between the observed failure-time data and the Weibull distribution. The estimated Weibull parameters were $\beta = 0.490009$ and $\eta = 5448.07$ h, resulting in an MTBF of 11,317.6 h.

These results form the basis for the subsequent reliability, availability, and preventive maintenance interval analyses. A summary of the MTTR and MTBF analysis results is presented in Table 9.

Tab.9. Summary of MTTR and MTBF Parameters for Critical GTG Components

Data	Component	β	η (h)	Anderson–Darling (AD)	Correlation Coefficient	MTTR	MTBF
TTR	Control System	1,46429	20,5916	1,102	0,977	18,6460	-
	Turbine	1,64517	97,7145	1,192	0,979	87,3980	-
	Combustor	2,52433	79,7530	1,852	0,979	70,7792	-
TTF	Control System	1,04468	2719,18	0,958	0,989	-	2672,04
	Turbine	1,45295	2623,64	1,584	0,964	-	2378,24
	Combustor	0,490009	5448,07	2,134	0,949	-	11317,6

The estimated Weibull shape parameter (β) revealed distinct failure behaviors among the critical GTG components. The Control System exhibited a β value of 1.04468, indicating an approximately constant failure rate and suggesting that failures occur predominantly in a random manner. In contrast, the Turbine showed a β value of 1.45295, indicating an increasing failure rate associated with degradation and wear-out mechanisms. The Combustor yielded a β value of 0.490009, reflecting a decreasing failure rate characteristic of early-life failures.

These results indicate that the critical components are subject to different failure mechanisms and therefore require different maintenance priorities. The Control System mainly requires condition monitoring and routine preventive maintenance, whereas the Turbine demands greater attention to age-related degradation through scheduled maintenance and component replacement. For the Combustor, maintenance efforts should focus on early-stage inspections and quality control measures to minimize premature failures.

Overall, the Weibull analysis demonstrates that a uniform maintenance policy may not adequately address the diverse failure characteristics of the critical GTG components. Consequently, component-specific reliability characteristics should be considered when determining preventive maintenance intervals and developing maintenance strategies.

3.7 Availability and Reliability Analysis

The availability and reliability of the critical GTG components were evaluated using the estimated MTBF, MTTR, and Weibull parameters obtained from the previous analyses. These indicators were used to assess component operational performance and maintenance effectiveness and to support the determination of appropriate preventive maintenance intervals.

The calculated availability and reliability values provide quantitative measures of component performance under the existing maintenance policy. The results were subsequently used to identify opportunities for reliability improvement and to evaluate the need for preventive maintenance interval optimization. The availability results for the Control System, Turbine, and Combustor are presented below.

1. *Availability of Control System*

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$$Availability = \frac{MTBF}{(MTBF + MTTR)}$$
$$= \frac{2672,04}{(2672,04 + 18,65)}$$
$$= \frac{2672,04}{2690,69}$$
$$= 0,9931$$
$$= 99,31\% \quad (4)$$

2. *Availability of Turbine*

$$Availability = \frac{MTBF}{(MTBF + MTTR)}$$
$$= \frac{2378,24}{(2378,24 + 87,40)}$$
$$= \frac{2378,24}{2465,64}$$
$$= 0,9646$$
$$= 96,46\% \quad (5)$$

3. *Availability of Combuster*

$$Availability = \frac{MTBF}{(MTBF + MTTR)}$$
$$= \frac{11317,60}{(11317,60 + 70,78)}$$
$$= \frac{11317,60}{11388,38}$$
$$= 0,9937$$
$$= 99,38\% \quad (6)$$

To assess the effectiveness of the current maintenance policy, the reliability of the three critical GTG components was evaluated at an operating time of 4,000 h, corresponding to the existing preventive maintenance interval adopted by the company. Reliability was estimated using the Weibull reliability function and the fitted Weibull parameters (β and η) obtained from the TTF analysis. The calculated reliability values are presented in the following section.

1. *Reliability of Control System*

$$R(t) = e^{-(t/\eta)^{\beta}}$$
$$R(4000) = 2.71828^{-(4000/2719.18)^{1.04468}}$$
$$= 2.71828^{-(1.471032)^{1.04468}}$$
$$= 2.71828^{-1.496619}$$
$$= 0.223886$$
$$= 22.39\% \quad (7)$$

2. *Reliability of Turbine*

$$R(t) = e^{-(t/\eta)^{\beta}}$$
$$R(4000) = 2.71828^{-(4000/2623.64)^{1.45295}}$$
$$= 2.71828^{-(1.524599)^{1.45295}}$$
$$= 2.71828^{-1.845509}$$
$$= 0.157945$$
$$= 15.79\% \quad (8)$$

3. *Reliability of Combuster*

$$R(t) = e^{-(t/\eta)^{\beta}}$$
$$R(4000) = 2.71828^{-(4000/5448.07)^{0.490009}}$$
$$= 2.71828^{-(0.734205)^{0.490009}}$$
$$= 2.71828^{-0.859507}$$
$$= 0.423371$$
$$= 42.34\% \quad (9)$$

The availability analysis showed that all critical components maintained high availability, reaching 99.31% for the Control System, 96.46% for the Turbine, and 99.38% for the Combustor. In contrast, the reliability values at the current preventive maintenance interval of 4,000 h were relatively low, at 22.39%, 15.79%, and 42.34%, respectively.

These results indicate that, although the components can be restored to operation efficiently following failures, the probability of failure-free operation up to the scheduled maintenance interval remains low. Therefore, the existing 4,000-h maintenance interval is not adequate to maintain the reliability of the critical GTG components. This finding highlights the need for PM interval optimization to improve reliability and reduce the risk of unplanned downtime.

Tab.10. Summary of Availability and Reliability Parameters at a 4,000-h Maintenance Interval

Parameter	Control System	Turbine	Combustor
Availability	99.31%	96.46%	99.38%
Reliability	22.39%	15.79%	42.34%

3.8 Preventive Maintenance Interval Determination The optimal inspection interval for each critical

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component was determined using the RCM-based inspection model, considering the average operating time, failure rate, repair rate, and inspection duration. The GTG system operates continuously at approximately 720 h/month, which was used as the basis for all calculations.
For the Control System, a total of 17 failures were recorded during the 60-month observation period, resulting in a failure rate of 0.28 failures/month. Based on an MTTR of 18.65 h and an average inspection time of 6 h, the calculated optimal inspection frequency was 0.9384 inspections/month, corresponding to an inspection interval of 767.3 h (approximately 32 days).
For the Turbine, 13 failures were observed during the study period, yielding a failure rate of 0.22 failures/month. Using an MTTR of 87.40 h and an average inspection duration of 16 h, the optimal inspection frequency was estimated at 1.0879 inspections/month, resulting in an inspection interval of 661.83 h (approximately 27.6 days).
Similarly, the Combustor experienced 7 failures over the observation period, corresponding to a failure rate of 0.12 failures/month. Based on an MTTR of 70.78 h and an average inspection time of 7 h, the optimal inspection frequency was calculated as 1.0861 inspections/month, equivalent to an inspection interval of 662.91 h (approximately 28 days).
The results indicate that the optimal preventive maintenance intervals differ among the critical components due to variations in their failure and repair characteristics. The Control System exhibited the longest recommended interval (767.3 h), whereas the Turbine and Combustor required more frequent maintenance, with intervals of 661.83 h and 662.91 h, respectively. These results provide the basis for the subsequent evaluation of maintenance scenarios and the development of an integrated group maintenance strategy.
Preventive maintenance interval optimization was conducted to establish maintenance schedules that better reflect the actual reliability characteristics of the critical GTG components. By performing maintenance before the probability of failure increases significantly, the proposed intervals are expected to enhance system reliability and minimize unplanned downtime.
The optimized PM intervals obtained for the Control System, Turbine, and Combustor are presented in the following section. These results serve as the basis for the subsequent evaluation of maintenance scenarios and the development of a group maintenance strategy at the system level.

Tab.11. Optimized PM Intervals for Critical GTG Components

Critical Components	Optimized PM Interval
Control System	767 hours
Turbine	662 hours
Combustor	663 hours

3.9 Proposed Preventive Maintenance Optimization Model

To establish an appropriate preventive maintenance policy, several maintenance interval scenarios were evaluated by comparing the reliability levels of the critical GTG components under different maintenance intervals. Reliability values were estimated using the Weibull reliability function and the corresponding parameters obtained from the TTF analysis. This evaluation provided a quantitative basis for assessing the effect of maintenance intervals on component reliability and identifying the most suitable maintenance policy.
The analysis focused on the Control System, Turbine, and Combustor, which were previously identified as the most critical components. The individually optimized PM intervals obtained from the reliability analysis were 767 h, 662 h, and 663 h, respectively. Because these intervals differed only marginally, a group maintenance approach was adopted to synchronize maintenance activities across the critical components.
The group maintenance approach enables multiple components to be maintained within a common maintenance window, thereby reducing scheduling complexity, improving resource utilization, and minimizing operational disruptions. Alternative maintenance interval scenarios were subsequently evaluated to identify an integrated maintenance interval that provides an appropriate balance between reliability performance and maintenance efficiency.

Tab.12. Reliability of Critical GTG Components Under Different Maintenance Interval Scenarios

% Interval PM	t (*hour*)	*Reliability*		
		Control System	*Turbine*	*Combustor*
100%	4000	22.39%	15.79%	42.34%
95%	3800	24.21%	18.03%	43.25%
90%	3600	26.17%	20.52%	44.21%
85%	3400	28.28%	23.29%	45.22%

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80%	3200	30.56%	26.33%	46.28%
75%	3000	33.02%	29.67%	47.40%
70%	2800	35.66%	33.32%	48.59%
65%	2600	38.51%	37.27%	49.86%
60%	2400	41.57%	41.54%	51.21%
55%	2200	44.87%	46.11%	52.66%
50%	2000	48.41%	50.96%	54.23%
45%	1800	52.21%	56.08%	55.92%
40%	1600	56.29%	61.42%	57.78%
35%	1400	60.66%	66.93%	59.82%
30%	1200	65.35%	72.55%	62.10%
25%	1000	70.35%	78.17%	64.68%
20%	800	75.69%	83.69%	67.66%
15%	600	81.36%	88.94%	71.23%
10%	400	87.37%	93.70%	75.72%
5%	200	93.66%	97.65%	82.03%
0%	0	100.00%	100.00%	100.00%

The results indicate that shorter preventive maintenance (PM) intervals result in higher component reliability. As the PM interval decreases, the probability that a component will continue operating without failure until the next scheduled maintenance activity increases. This finding confirms the inverse relationship between PM interval length and reliability.

Under the current maintenance policy of 4,000 h, the reliability values were relatively low, reaching only 22.39% for the Control System, 15.79% for the Turbine, and 42.34% for the Combustor. These results suggest that a substantial proportion of failures are likely to occur before the next scheduled maintenance activity.



Fig.16. Relationship Between Preventive Maintenance Interval and Reliability of Critical GTG Components

The individual PM interval optimization results indicated optimal maintenance intervals of 767 h for the Control System, 662 h for the Turbine, and 663 h for the Combustor. However, implementing these intervals separately would require different maintenance schedules for each component, resulting in increased maintenance complexity and resource requirements. Therefore, a group maintenance approach was evaluated by comparing several integrated maintenance interval scenarios.

The results shown in Table 12 and Figure 16 indicate that shorter PM intervals lead to higher reliability levels, whereas longer intervals significantly reduce component reliability. Based on the scenario evaluation, a maintenance interval of 600 h was selected as the most appropriate group maintenance interval because it provides the best balance between reliability improvement and operational efficiency.

Compared with shorter intervals of 200 h and 400 h, the 600-h interval maintains high reliability while reducing the frequency of maintenance interventions. At the same time, it offers substantially higher reliability than longer intervals ranging from 800 h to 4,000 h, thereby reducing the likelihood of failure during operation. In addition, the selected interval is close to the individually optimized PM intervals obtained through the RCM analysis, allowing maintenance to be performed before a significant decline in reliability occurs.

The adoption of a 600-h maintenance interval also facilitates the implementation of group maintenance by enabling all critical components to be serviced within a common maintenance schedule. This approach improves maintenance planning, optimizes resource utilization, and minimizes operational disruptions while maintaining acceptable reliability levels.

The reliability values at the selected 600-h maintenance interval were calculated based on Tabel 12. The results yielded reliability levels of 81.36% for the Control

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System, 88.94% for the Turbine, and 71.23% for the Combustor. These values are substantially higher than those obtained under the existing 4,000-h maintenance interval, demonstrating the effectiveness of the proposed maintenance strategy in improving GTG reliability while maintaining maintenance efficiency.

As a result, the 600-h group maintenance interval is recommended as the optimal maintenance policy for the GTG system because it provides the most favorable compromise between reliability performance, maintenance frequency, and practical implementation requirements.

4. Conclusion

This study applied Failure Mode and Effects Analysis (FMEA) and Reliability-Centered Maintenance (RCM) to assess failure risks, evaluate component reliability, and optimize preventive maintenance (PM) intervals for the Gas Turbine Generator (GTG) system at PT XYZ. The FMEA results identified the Control System, Turbine, and Combustor as the most critical components, with RPN values of 320, 280, and 240, respectively.

Reliability analysis revealed that, despite the high availability of the critical components, the existing 4,000-h maintenance interval resulted in relatively low reliability levels, indicating that the current maintenance policy does not adequately reflect the actual failure characteristics of the GTG system. The optimal PM intervals obtained from component-level analysis were 767 h for the Control System, 662 h for the Turbine, and 663 h for the Combustor.

To improve maintenance effectiveness at the system level, a group maintenance approach was implemented. Based on the evaluation of alternative maintenance scenarios, a unified maintenance interval of 600 h was selected as the most suitable maintenance policy. This interval increased component reliability to 81.36%, 88.94%, and 71.23% for the Control System, Turbine, and Combustor, respectively, while simplifying maintenance scheduling and reducing the risk of unplanned downtime.

The main contribution of this study is the development of a data-driven maintenance decision framework that integrates failure risk assessment, reliability analysis, PM interval optimization, and group maintenance scheduling. The proposed approach provides a practical strategy for improving reliability and maintenance performance in continuously operating GTG systems and can serve as a reference for reliability-based maintenance planning in similar industrial applications.

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