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Reliability enhancement in the petrochemical industry: an integrated RBD and FTA approach

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Abstract

Turnaround maintenance plays a crucial role in the petrochemical industry, directly impacting production reliability and operational continuity. Unplanned shutdowns and service disruptions can lead to substantial economic losses. Yet, statistics show that nearly 80% of turnaround activities fail to achieve their performance targets in terms of time, cost, safety, quality, and environmental compliance. This study addresses these challenges by evaluating and enhancing the reliability of the ammonia production system at an Indonesian petrochemical company through an integrated approach combining the Reliability Block Diagram (RBD) and Fault Tree Analysis (FTA). RBD modeling was used to represent the production system as functionally arranged blocks, while FTA was applied to identify root causes of failures. Analysis using ReliaSoft® BlockSim and Weibull++® revealed that the system's reliability was only 0.029 over 5000 hours, far below the target reliability of 0.9. The most critical components were identified as the primary reformer, ammonia compressor, and syngas compressor. Seven improvement scenarios were simulated, with results showing that the combination of Preventive Maintenance (PM) and load-sharing configuration yielded the most effective outcome. This approach improved reliability to 0.076 and availability to 0.812. The results show that a proactive, reliability-based maintenance strategy, combined with system redundancy, can substantially reduce the risks of unscheduled shutdowns, extend turnaround intervals, and improve production uptime. Furthermore, the integrated RBD-FTA approach provides a robust framework for proactively identifying and addressing vulnerabilities in complex petrochemical systems.

Keywords:
FTA, PM, petrochemical, RBD, TAM

1 Introduction

The petrochemical industry plays a crucial role in facilitating economic processes and driving innovation. This is due to its broad scope, which encompasses various types of enterprises directly or indirectly involved in the production of oil and natural gas, as well as its adoption in products closely related to human needs, such as pharmaceuticals, fertilizers, explosives, insulation materials, plastics, fibers, synthetic rubber, and others. Although its primary feedstocks are still derived from oil and natural gas due to their relatively low cost, readiness for use, and ease of processing, alternative feedstocks can also be sourced from more renewable resources, such as corn and sugarcane [1], [2]. The petrochemical industry is a cornerstone of modern economies, providing essential building blocks for various sectors, from pharmaceuticals to plastics [3]. These plants must maintain reliable performance to support overall business processes.

Performance reliability, defined as the measurement of a feature's ability to function as intended, is paramount in the petrochemical industry [4]. These industries often employ continuous flow production models, making the turnaround a key operational attribute. Turnarounds, which involve upgrades, modifications, repairs, and maintenance of system components, are essential for ensuring the continued safe, efficient, and reliable operation of petrochemical facilities. Plants must maintain an optimal turnaround time, as delays can lead to substantial production and economic losses. Moreover, companies are focusing on asset reliability and performance, utilizing technologies such as IoT and remote monitoring to enhance asset dependability [5]. A significant challenge is that approximately 80% of turnaround activities fail to meet performance indicators related to time, cost, safety, quality, and environmental standards [6]. This failure rate highlights the need for improved turnaround planning and execution to minimize disruptions and economic losses. Therefore, this research is important because it addresses the critical need to enhance system reliability through the integrated use of Reliability Block Diagram (RBD) and Fault Tree Analysis (FTA). While the separate application of RBD and FTA is well-established, their combined use, particularly in the petrochemical industry, is still limited. This study contributes to the field by offering a robust framework for proactively identifying and addressing vulnerabilities in complex petrochemical systems, thereby optimizing maintenance strategies and minimizing the risk of unscheduled shutdowns.

One of the fundamental principles of reliability analysis is to identify and measure system failures. This is achieved through various intervention actions (e.g., preventive, control, and mitigative) aimed at reducing the likelihood of failure and associated risk levels to an acceptable threshold, As Low As Reasonably Practicable (ALARP) [7]. FTA is a structured and standardized method used to analyze undesired events and the likelihood of their occurrence. This method can be employed both to anticipate and prevent potential problems and to investigate issues that have already occurred. FTA is easy to understand and apply while still offering valuable insights by encompassing all possible causes related to the analyzed top event. It is also time- and resource-efficient, as it focuses directly on the top event [8]. However, FTA as a method lacks a rigid analytical framework and does not provide a more comprehensive evaluation or broader contextual consideration [9].

A method that can provide a comprehensive explanation of system reliability is the RBD. RBD is a technique used to analyze system reliability by considering the availability of large and complex systems through the use of system blocks. It graphically represents the system components and their contributions to the overall system reliability. RBD enables reliability prediction by breaking down the system into smaller, manageable block components, thereby predicting the reliability of individual components. It helps identify weak points or vulnerabilities within the system that may lead to failure, thereby allowing for targeted improvements to enhance overall reliability [10], [11], [12]. The combination of the FTA and RBD methods can offer a holistic system analysis, along with a comprehensive and in-depth discussion of individual units within the system.

The implementation of both methods to improve system reliability has been widely applied across various industrial sectors, including the petrochemical industry. Zacchaeus et al. [13] applied the FTA method to analyze operational risks related to safety and efficiency in Nigeria's oil and gas industry. The analysis addressed a range of incidents, from structural failures to safety risks. The use of FTA enabled the identification of system weaknesses and supported the development of corrective strategies to enhance safety protocols. Meanwhile, Zuo et al. [14] adopted the RBD method to analyze the reliability and safety of pressurized tubing instrumentation systems in subsea oil and gas production processes. Their findings demonstrated that the modified reliability model was more accurate and more practical for engineering applications.

Simultaneously, Jakkula et al. [15] combined FTA and RBD methods for the maintenance system of Load-Haul-Dumpers (LHDs) in underground mining operations. FTA was used to assess LHD system reliability based on functional flow diagrams, while RBD was employed to configure the reliability of each LHD system. The use of RBD showed a maximum reliability rate of 69.44%, whereas FTA produced a peak reliability rate of 79.51%. These techniques helped identify the most critical system components or subsets. Although the simultaneous implementation of both methods in the petrochemical industry is still limited, it holds significant potential for broader development.

The research was conducted at one of the petrochemical production companies in Indonesia. The objective of the study is to enhance system reliability by modeling the existing system using the RBD and FTA methods, as well as by developing scenarios for improving maintenance processes within the turnaround interval without causing unscheduled shutdowns. Preventing unscheduled shutdowns is of critical importance, as they are a primary cause of service disruptions and machinery damage [16]. The improvements are expected to reduce operational risks by increasing overall system reliability.

2 Research methodology

The study was conducted as a case study on the maintenance management system of a petrochemical plant. This approach allowed for an in-depth investigation of a real-world scenario, providing rich, contextualized data. Reliability analysis was performed by illustrating the relationship between each component and its contribution to the overall system reliability. Data collection involved observing the operational maintenance management system of the petrochemical plant by analyzing incidents, their causes, and the frequency of downtime events that occurred over the past decade, specifically from 2014 to 2024. This quantitative data on downtime events was crucial for understanding the system's historical performance. The RBD method was employed to describe and explain the system's reliability, taking into account all components within the system [17]. The RBD method was applied by dividing the system into individual parts (e.g., components, equipment, groups of components), which were represented in the form of blocks as illustrated in Fig. 1 [18]. This visual representation facilitated the analysis of each system component and examination of how the reliability of individual components influences the overall reliability of the petrochemical production system.

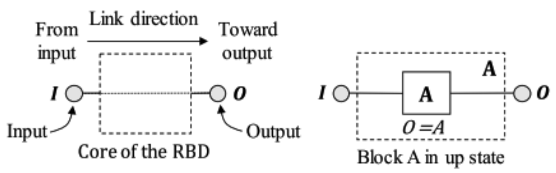

Fig. 1. RBD model

The development of the RBD model was carried out based on the following assumptions:

1. The system and each component are modeled using only two conditions: success and failure.
2. The RBD represents the successful state of the modeled system through the use of success paths.
3. The system components are statistically independent, meaning the failure probability of one block is not related to the failure probability of other blocks [19].

The general reliability concept was structured based on the k-out-of-n configuration principle, where k represents the minimum number of components (elements) required for successful operation, and n denotes the total number of available components in the system under regular operation. A statistical approach was employed, utilizing the failure time distribution and its parameters to assess the system's reliability. Commonly used distributions in reliability analysis include various continuous probability functions, such as Exponential, Rayleigh, Weibull, and Uniform distributions. Reliability parameters are derived based on the characteristics of each distribution type [20].

The determination of both the distribution type and its parameters for calculating time between failures was performed using ReliaSoft® Weibull++® software. Weibull++® is used to identify and select the most appropriate distribution model, offering the capability to generate precise failure rate estimates, hazard rate modeling, and component criticality ranking. These capabilities make Weibull++® one of the leading tools in reliability engineering research [21], [22].

This study employs the FTA method to identify potential causes of failure within the system. FTA is a deductive failure analysis method that utilizes a top-down approach and Boolean logic to understand the causes of system failure and to find the best solutions for reducing failure risks or confirming the occurrence rate of a specific safety risk or system failure [23]. FTA is based on a hierarchical structure of relationships between each failure and the underlying influencing factors that are not directly observable. It analyzes scenarios involving undesired events to uncover all realistic pathways and reasons behind their occurrence.

FTA provides a graphical analytical tool for exploring the root causes of failures at the system level [24], [25], [26]. It uses illustrations in the form of logic gates and represents system failure causes as a top event. A conventional example of FTA implementation is shown in Fig. 2 [27].

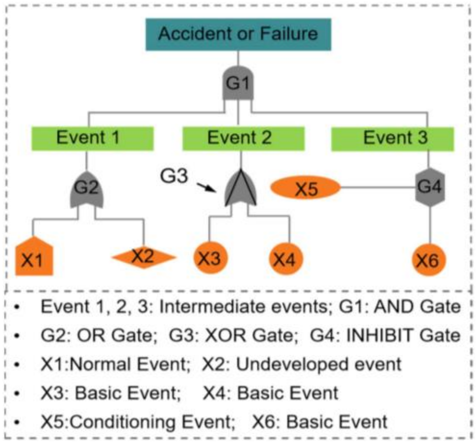

Fig. 2. FTA model

The application of the FTA method in system reliability analysis does not follow a rigid guideline, but it generally involves the following steps [28], [29]:

1. Identify or select the top event
2. Events are evaluated based on their significance and patterns. The most critical undesired event that causes system failure is defined as the top event, which serves as the starting point for risk analysis.
3. Identify events and causes
4. Determine the root causes that could lead to the top event. This may include analyzing data from accident reports, incident databases, or conducting expert interviews to gain a deeper understanding of the issue.
5. Construct the fault tree diagram.
6. Illustrate the relationships between the top event and potential causes, connecting them through logic gates.
7. Evaluate or quantify the fault tree.
8. Calculate the event occurrence rate based on the frequency of individual contributing factors, starting from the most basic level. This step aims to identify potential improvements that can mitigate risks.
9. Control or assess hazard risks
10. Perform a risk assessment based on the calculated event occurrence rates to reduce the likelihood of undesired events.

In this study, system modeling was conducted using both the RBD and FTA methods with ReliaSoft® BlockSim software to ensure greater modeling precision. BlockSim® allows for the computation and analysis of complex systems, the construction of intricate Fault Tree models, and the application of probabilistic inputs for each component block [30], [31]. The analysis in this research was performed to optimize the Turnaround Maintenance (TAM) interval to minimize the risk of failure in system operations [32], [33].

3 Results and discussion

3.1 System downtime event

Observations conducted found downtime in the petrochemical production system. The downtime was caused by various constraints in each subsystem, which were further described in Table 1.

Table 1. Downtime & frequency sub-system

Sub system	Downtime (hours)	Frequency
Air compression	125.76	4
Steam generation	687.84	5
Power generation	706.8	7
Reforming system	1544.88	10
Refrigerant compression	57.84	3
Syngas compression	663.84	17

To provide a detailed overview of the downtime events, data from 2014 to 2024 is presented in Table 2. Based on downtime data observed from 2014 to 2024, each subsystem within the chemical plant's production process contributed differently to operational disruptions. The total downtime across all systems reached 3, 3787.96. 96 hours, with variations in both the duration and frequency of incidents.

Table 2. Overview of downtime & frequency sub-system

No	Sub system	Downtime start date	Downtime end date	Downtime duration (hours)	Cause of failure
1	Reforming system	16/12/2013	01/01/2014	384	Superheated tube coil broken
			….		
9	Power generation	29/03/2015	31/03/2015	52.08	GTG-2 Trip
			….		
12	Syngas compression	04/01/2016	04/01/2016	5.04	61-103-JT trip (TAHH 4283 - false alarm indication)
			….		
17	Syngas compression	27/06/2017	28/06/2017	7.44	51-103-J (Syn gas compressor) trip - Instrument failure
			….		
19	Power generation	09/03/2018	10/03/2018	18.48	Electrical failure
			…		
24	Syngas compression	03/01/2019	04/01/2019	18.96	Fixing 61-SV-1213
			….		
35	Syngas compression	08/11/2020	08/11/2020	18.24	Fixing balancing line Compressor Syngas (61-103-J)
			….		
43	Power generation	31/12/2021	31/12/2021	23.28	Power Failure
			….		
48	Syngas compression	01/11/2022	04/11/2022	88.32	Hold start, 103 JT Trip Vibrasi VAHH-4206 and VAHH-4204
			….		
55	Reforming system	27/11/2023	29/11/2023	36.24	Speed ID fan in primary reformer increases suddenly, and Combustion Air decreases so that PALL 1231 interlock is Active
			….		
60	Steam generation	01/12/2024	02/12/2024	39.36	PB-2 got an issue

The Reforming System was identified as the largest contributor to total downtime, with a combined disruption time of 1, 1544.88. 88 hours. This accounts for approximately 40. 8% of the total downtime, making it the most critical component affecting production efficiency. Although there were only 10 failure events, each caused a relatively long disruption, indicating that failures here are complex and require extensive repairs. As a result, reforming this system is the main focus of the strategy to improve overall reliability.

In contrast, the syngas compression subsystem displayed different failure characteristics. With the highest number of incidents- 17 occurrences- Syngas Compression was the most frequently disrupted component, although its total downtime was only 663. 84 hours, ranking fourth overall. The high frequency suggests recurring issues that threaten production continuity. Therefore, preventive measures and regular inspections should be strengthened in this subsystem to reduce breakdowns.

Other subsystems, such as power generation and steam Generation, also contributed significantly, with totals of 706. 8 hours and 687. 84 hours, respectively, and moderate failure frequencies. Although failures in these energy systems were less frequent than in syngas compression, their incidents still had a considerable impact due to their longer durations. Meanwhile, air compression and refrigerant compression experienced relatively low durations and failure frequencies, making them lower priorities for intervention.

Overall, the analysis indicates that efforts to improve system reliability should mainly target two subsystems: reforming system and syngas compression. The reforming system should be prioritized based on total downtime, while syngas compression needs attention due to its high failure frequency. This approach aligns with the Pareto principle, which suggests that most problems (about 80%) are caused by a small number of key factors (around 20%). The Pareto diagram of plant downtime is presented in Fig. 3.

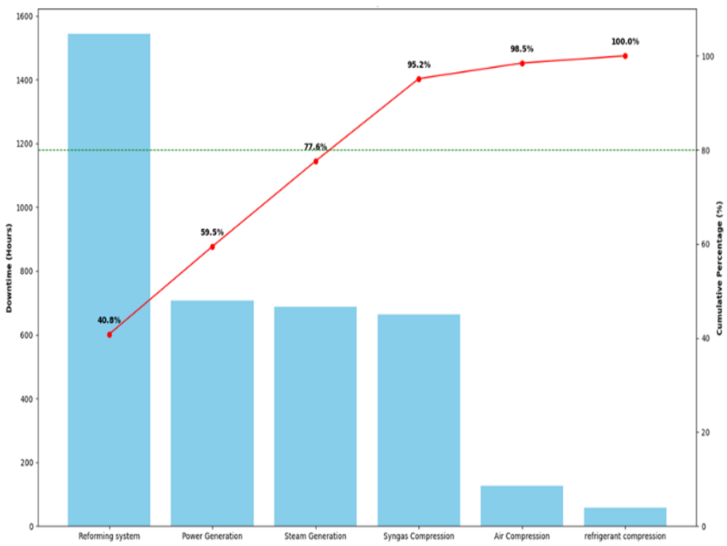

Fig. 3. Pareto downtime

3.2 RBD and calculating reliability

RBD is modeled using BlockSim® 2024 software. Fig. 4 shows the RBD of a petrochemical plant production system, with each block representing each piece of equipment arranged in series.

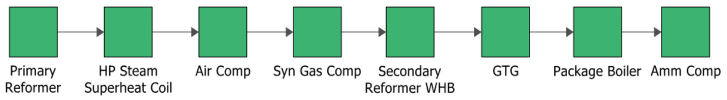

Fig. 4. Petrochemical production RBD model

This series arrangement can be interpreted that all models must work or function normally as a whole so that the system is able to carry out its function. Failure or constraints experienced by one of the equipment will cause failure of the entire system. Analysis is carried out on the RBD that has been modeled by comparing the level of reliability to operational time, as shown in Fig. 5.

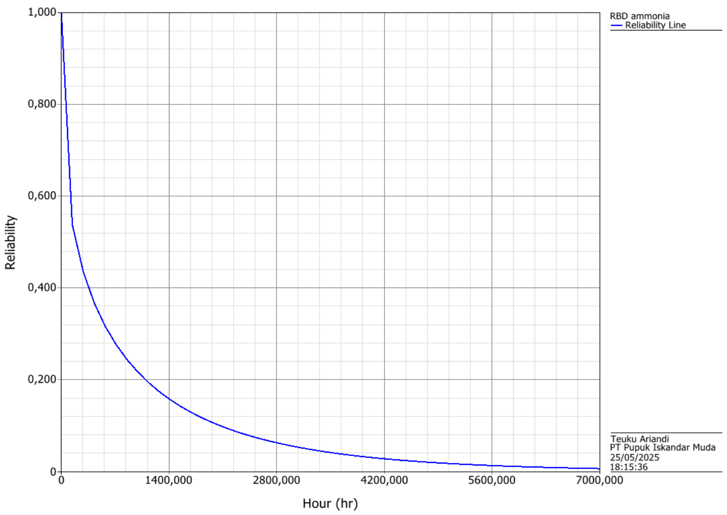

Fig. 5. System reliability vs time comparison chart

Comparison of reliability over time shows that the system's reliability decreases as the production operating time increases without TAM, with the system reaching a reliability level of 0 after 7,000 hours of production. This study examines system reliability over 5000 hours. The 5000-hour time horizon is chosen based on the average effective operating time of petrochemical production systems within an annual turnaround cycle, which typically ranges from 4000 to 6000 hours. This period marks a critical point in the component failure distribution, where system reliability begins to decline notably. Additionally, using a 5000-hour horizon aligns with industry standards and prior research on evaluating system reliability improvement strategies [5]. The current reliability level of the petrochemical plant's production system is 0.029652 for a 5000-hour production run. The target reliability level to be achieved for optimal performance is 0.9 over 5000 hours of operation. This serves as the basis for the repair simulation to determine the optimal treatment.

3.3 Reliability importance

Reliability Importance (RI) is a method used to assess the contribution of individual components to the overall system reliability by classifying them based on the extent to which their condition affects system reliability. The primary goal of RI analysis is to identify the most critical components and the weakest parts of the system by considering the impact of risk factors on the system and quantifying the effect of component failures on overall performance [34], [35], [36], [37]. In this study, the RI analysis of the petrochemical plant production system was carried out using static RI techniques, as illustrated in Fig. 6.

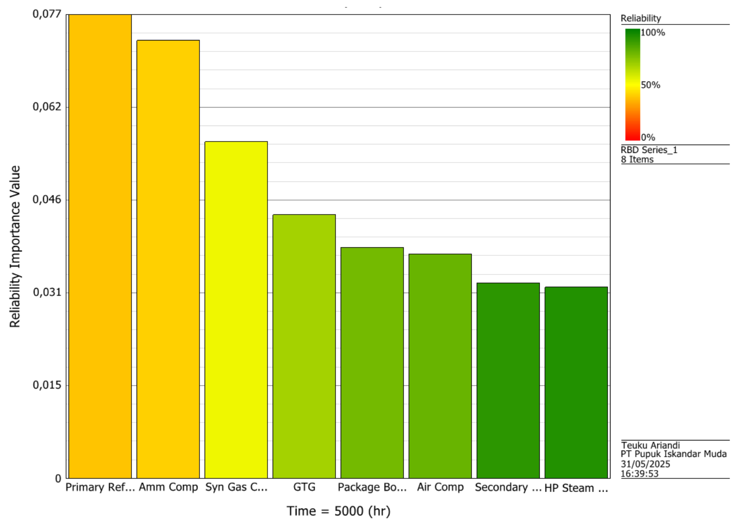

Fig. 6. System RI chart

The results of the Static RI analysis at 5000 hours of operation indicate that each subsystem within the production system exhibits varying degrees of influence on the overall system reliability. According to the chart, the primary reformer and ammonia compressor equipment possess the highest importance values, suggesting that any improvement in the reliability of these components will significantly enhance the total system's reliability. Consequently, these two subsystems can be classified as critical components and should be given top priority in the planning of Reliability-Centered Maintenance (RCM) strategies.

Other equipment, such as the syngas compressor, Gas Turbine Generator (GTG), and package boiler, ranks in the medium tier in terms of reliability importance. Although their contribution to total system reliability is not as substantial as the top two components, they remain essential for ensuring operational continuity. As such, Preventive Maintenance (PM) and routine condition monitoring are still required to prevent progressive performance degradation. Meanwhile, subsystems such as the air compressor, secondary system, and high-pressure steam system exhibit relatively lower importance values. This indicates that fluctuations in the reliability of these subsystems do not significantly impact the overall system reliability. Nonetheless, supervision and maintenance are still necessary as part of a systematic approach to avoid the accumulation of undetected risks.

The RI vs. time graph in Fig. 7 indicates that all subsystems exhibit an exponential decline in RI values throughout system operation. This trend reflects that the relative contribution of each component to overall system reliability diminishes as the system ages.

In the early phase (0–2000 hours), the differences in importance values between components are highly pronounced, indicating that the system is still in a sensitivity phase, where reliability heavily depends on its critical components. However, at 5000 hours, the graph shows that while the rate of decline begins to slow, the distribution of importance values among components remains distinct.

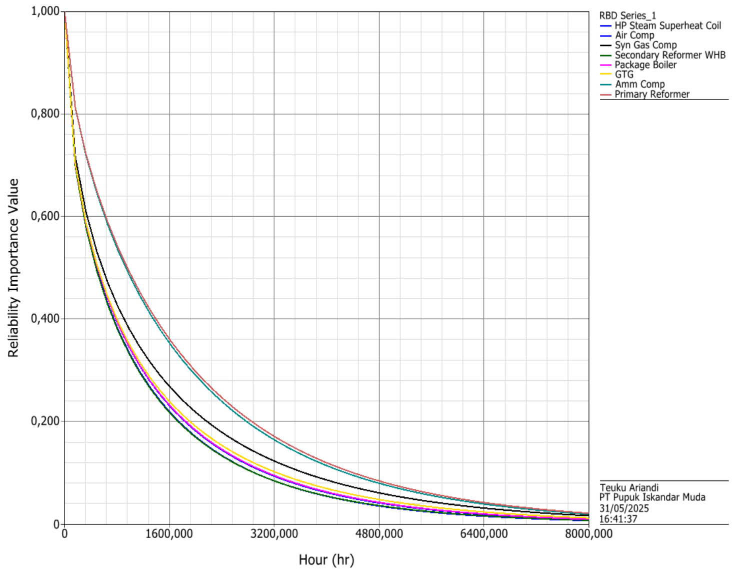

Fig. 7. RI vs time system chart

At this point, equipment such as the primary reformer, ammonia compressor, and syngas compressor still exhibit relatively higher importance values compared to other components like the HP steam superheat coil and air compressor, whose contributions to system reliability have become significantly lower.

3.4 Reliability allocation

Reliability allocation is determined to find equipment that needs to be increased in reliability value based on several factors, such as cost factors, reliability importance, and difficulty in implementation. This aims to achieve the target reliability value by increasing equipment reliability based on its criticality level. Reliability allocation is calculated using BlockSim® 2024 software. Reliability allocation system recapitulation can be seen in Table 3.

Table 3 presents the results of the reliability evaluation for each subsystem configured in a series system, analyzed at 5,000 hours of operation using the RBD model. The table includes key parameters such as RI, the actual reliability values of each subsystem, the target system reliability, and the equivalent number of parallel units required to achieve the desired reliability target.

Table 3. Reliability allocation system recapitulation

Block name	Reliability index (5000)	Reliability (5000)	Probability of failure
HP steam superheat coil	0,031747	0,934001	0,0660
Air comp	0,037285	0,795276	0.2047
Syn gas comp	0,055869	0,530738	0.4693
Secondary reformer WHB	0,032434	0,914219	0.0858
Package boiler	0,03834	0,773381	0.2266
GTG	0,043754	0,677681	0.3223
Amm comp	0,072703	0,407846	0.5922
Primary reformer	0,077039	0,38489	0.6151

The analysis reveals that the primary reformer, ammonia compressor, and syngas compressor have the highest RI values, at 7.70%, 7.27%, and 5.59%, respectively. These values suggest that even minor improvements in the reliability of these components will have a substantial impact on enhancing the overall system reliability. In contrast, components such as the HP steam superheat coil and secondary reformer Waste Heat Boiler (WHB), despite having relatively high intrinsic reliability values (0.934 and 0.914, respectively), contribute less to the system's reliability due to their relatively lower RI values. A summary of block performance for each equipment component, based on simulation results, is illustrated in the Failure Reporting, Evaluation, and Display (FRED) report shown in Fig. 8.

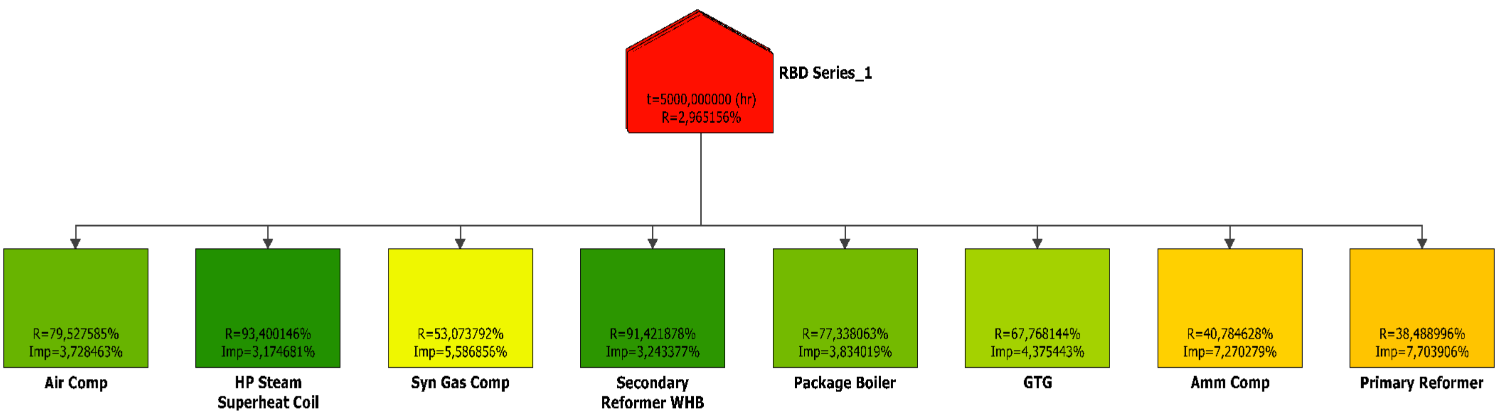

Fig. 8. FRED report system

3.5 Improvement of reliability

Various treatments are implemented in the simulation scenario to increase the reliability of the observed system. Simulation with scenarios is carried out to compare the reliability of the system at the initial condition before the intervention with various alternative treatments that can be taken. The alternative scenarios include the addition of Corrective Maintenance (CM), the addition of parallel models, the division of workloads in a balanced or controlled manner between two or more equipment in a parallel system (load sharing), the addition of PM, the addition of a combination of PM and parallel models, and the combination of the addition of PM and load sharing models. Results of the reliability improvement scenarios can be seen in Table 4.

Table 4. Results of reliability improvement scenarios

No	Skenario	Reliability	Availability
1	Initial condition	0.029	0.202865
2	CM	0.035	0.73774
3	Parallel treatment	0.053	0.237508
4	Load sharing	0.046	0.22358
5	PM	0.064	0.811192
6	PM + Parallel treatment	0.07	0.811013
7	PM + Load sharing	0.076	0.81225

The initial condition serves as the baseline, representing a system without any maintenance strategy in place. It exhibits the lowest reliability and availability, rendering the system highly susceptible to failures and prolonged downtime. In the CM scenario, availability increases significantly because repairs are performed quickly after failures occur. However, reliability remains low as failures still happen frequently. The addition of a parallel model increases the system's chance of remaining operational even if one unit fails. Nonetheless, without any maintenance, downtime remains high despite the improved system redundancy.

In the Load Sharing scenario, where the load is distributed among Gas Turbine Generators (GTGs), reliability is slightly lower than in the parallel model. However, availability remains low in the absence of maintenance. The inclusion of PM significantly improves system reliability and reduces downtime. PM proves to be one of the most effective maintenance strategies, particularly when implemented routinely. The combined scenario of PM and parallel configuration yields a highly stable system, although there remains room for further optimization. Meanwhile, the combined PM and Load Sharing scenario represents an active strategy that combines load distribution and scheduled maintenance, resulting in the most optimal outcome overall. This scenario is especially suitable for critical systems that require high stability and minimal operational disruption.

Table 5 shows the top event, failure elements, and a description of the cause of the failure event. The top event was found to occur in the form of a failure of the entire production system, with the cause being the ammonia production system failing to operate thoroughly.

The FTA model (Fig. 9) is based on the logic of the Table 5 system, with the top event representing a significant failure of the entire system. The top event will occur if one of the formulated causes occurs; then the "OR Gate" logic gate is used. The results of the FTA calculation can be seen in Table 6.

Table 5. Top event and cause

Level	Elemen	Deskripsi
Top event	Production system failure	The ammonia production system fails to operate completely
Cause 1	Primary reformer failure	Catalyst tube failure
Cause 2	HP steam superheat coil failure	Finned tube failure
Cause 3	Air compressor failure	Control system failure
Cause 4	Syngas compressor failure	Bearing failure
Cause 5	Secondary reformer WHB failure	Tube failure
Cause 6	GTG failure	Control system failure
Cause 7	package boiler failure	Tube failure
Cause 8	Ammonia compressor failure	Control system failure

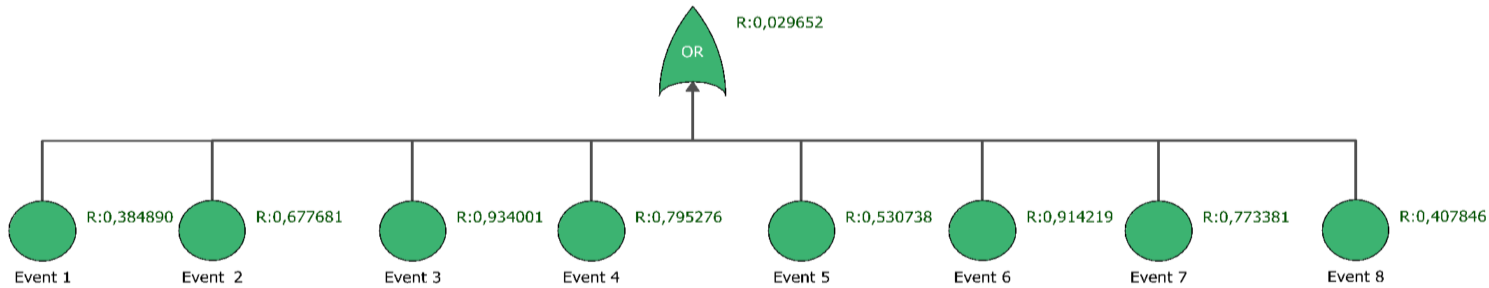

Fig. 9. Petrochemical production FT a model

Table 6. FTA

Block name	Reliability	Prob. of failure	Importance
OR	1	0	0
Event 1	0.38489	0.61511	0.077039
Event 7	0.773381	0.226619	0.03834
Event 8	0.407846	0.592154	0.072703
Event 5	0.530738	0.469262	0.055869
Event 3	0.934001	0.065999	0.031747
Event 4	0.795276	0.204724	0.037285
Event 6	0.914219	0.085781	0.032434
Event 2	0.677681	0.322319	0.043754
	Reliability	Prob. of failure	
System	0.029652	0.970348	

Table 6 presents the reliability level, probability of failure, and importance of each failure event. The component with the highest reliability is associated with Event 6, which corresponds to the GTG. Meanwhile, the highest probability of failure and importance are observed in Event 1, with a failure probability of 0.61511. Intervention efforts are focused on events with both high failure probability and high importance, specifically Events 1 and 8. This approach aligns with the findings of Katreddi et al. [38], who emphasized the importance of prioritizing corrective actions for failure events that demonstrate significant levels of importance and probability of occurrence.

4 Conclusions

This study evaluated the reliability of the Ammonia Unit at PT Pupuk Iskandar Muda using an integrated RBD and FTA approach. The assessment revealed a very low system reliability of 0.029 over a 5000-hour operational horizon, compared to the target of 0.9, underscoring a critical performance gap. Key components contributing to this low reliability were the primary reformer, ammonia compressor, and syngas compressor, all of which require prioritized interventions. Simulation of reliability improvement scenarios confirmed that PM significantly enhances both system reliability and availability. Notably, the combination of PM and load-sharing configuration provided the most effective improvement, raising reliability to 0.076 and availability to 0.812. These results demonstrate the strong potential of integrating proactive maintenance with redundancy strategies to improve operational resilience. The implications extend beyond immediate reliability improvements: adopting predictive and preventive approaches while exploring design modifications to add redundancy can ensure greater process continuity, minimize unplanned shutdowns, and extend turnaround intervals. Overall, this integrated methodology represents a robust framework for enhancing petrochemical system reliability and can serve as a model for other high-risk industrial operations.

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