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Integrating Life Cycle Management and Risk Assessment for Enhanced Investment in Power Plant Equipment Maintenance

Abstract
Investment decision-making in power plant sector significant challenges to technical risks and declining operational efficiency. Research is urgent because no integrative model that systematically combines technical and financial approaches in determining investment feasibility, particularly for critical components such as Blade Turbine at power plant. Objective of this study to identify dominant risk factors and assess investment feasibility based on historical data and asset life cycle analysis. The research method employs a concurrent mixed methods approach by integrating quantitative analysis Pareto Loss, Failure Mode, Life Cycle Management with qualitative insights Focuss Group Discussion, technical observation and validated through triangulation of source, time, and method. Results show that Mech-Looseness and Deformation are the main causes of derating, reaching up to 700 hours, decreasing efficiency and increasing Nett Plant Hour Rate. Financially, the investment is considered highly feasible, indicated by a positive Net Present Value, high Internal Rate of Return, short Payback Period, and favorable Benefit-Cost Ratio.This study offers strategic value by demonstrating that implementing Life Cycle Management integrated with Failure Mode and Pareto Loss can improve investment decision accuracy, extend asset lifespan and strengthen operational efficiency and sustainability of the power plant.

Keywords: Life Cycle Management, Risk Assesment, Investment, Power Plant, Maintenance.

1 Introduction

Energy sector is foundational to the interconnected dynamics of global economic activity, influencing both socioeconomic development and sustainability initiatives. In Indonesia, Steam Power Plants serve as a primary electricity source; however, they face significant challenges, including fluctuating energy prices and evolving regulatory landscapes Investment plays a crucial role in driving economic growth and ensuring business sustainability. On a global scale, the ability to make sound investment decisions remains one of the primary challenges faced by many companies (Nemade & Ponsankar, 2020). Strategic investment decisions can serve as a key driver in creating added value and maintaining operational stability (Dobrowolski & Drozdowski, 2022). These complications complicate investment decision-making processes significantly. Technological advancements in renewable energy systems offer both opportunities and risks, requiring significant investments in infrastructure and skills while potentially disrupting existing energy markets. Complex global economic dynamics, the energy sector plays a central role as it forms the foundation for various economic and social activities. However, this sector also faces significant challenges such as energy price fluctuations, regulatory changes, and technological advancements, all of which contribute to increasing complexity in investment decision-making (Nemade & Ponsankar, 2020). Steam Power Plants (PLTU) remain one of the dominant sources of electricity supply in Indonesia. Nevertheless, the sector is confronted with various challenges, including the sustainability of operations.

Power plant faces major challenges in maintaining operational efficiency and ensuring business sustainability. The ability to make informed investment choices can be significantly improved through structured decision-making frameworks (Dobrowolski & Drozdowski, 2022). These frameworks help prioritize investments that bolster profitability while contributing to long-term sustainability goals, thus addressing the complex challenges faced by power plant (Lipka & Szwed, 2021). Any investment made must contribute positively to profitability while also supporting environmental sustainability. One of the primary challenges in investment management is determining investment priorities that significantly impact both sustainability and efficiency (Ambarwati et al., 2022). The power plant sector faces various risks that can affect investment outcomes, including fluctuations in fuel prices, changes in government policies related to carbon emissions, and increasing pressure to transition to renewable energy technologies. Moreover, suboptimal lifecycle management of the power plant can lead to high maintenance costs and premature equipment failure before reaching its expected service life (Andespa et al., 2022). Moreover, ineffective lifecycle management in power plant operations can exacerbate financial challenges through increased maintenance costs and unexpected equipment failures. The failure to optimize the lifecycle of equipment not only leads to diminished operational efficiency but may also result in the premature retirement of key assets, preventing the plant from achieving its anticipated service life (Sowinski, 2022). The previous research has proactive and strategic approach to managing these lifecycle risks can enhance the sustainability and economic availability of power plants, ultimately leading to improved investment security in the sector (Benato et al., 2022)(Martiniello et al., 2020). The interplay of price volatility, regulatory changes and ineffective lifecycle management emphasizes the urgency for stakeholders in the power plant sector to adopt adaptive strategies. Through such measures, industry players can better position themselves to exploit opportunities while mitigating potential risks associated with traditional energy production, paving the way for a more resilient energy future (Rocha-Meneses et al., 2023).

Data-driven and analytical approach has become increasingly relevant in supporting investment decision-making. A data-driven and analytical approach, particularly utilizing the Pareto principle, has been demonstrated to be increasingly significant in enhancing investment decision-making processes. This principle indicates that a substantial proportion of outcomes derives from a minority of influential variables or factors. Within the investment framework, the Pareto principle serves as a tool for identifying and prioritizing essential factors that substantially impact investment success or failure. This prioritization allows organizations to allocate their resources effectively, ultimately leading to a reduction in losses stemming from potentially suboptimal investment decisions, as noted in studies advocating for strategic resource allocation in uncertain environments. One such approach that can be applied is the Pareto Loss method, based on the 80/20 principle (Wong, 2024). his principle suggests that a majority of outcomes or impacts typically stem from a small number of factors or variables. In the context of investment, Pareto Loss helps identify and prioritize the factors that have the most significant effect on the success or failure of an investment. By doing so, companies can allocate their resources more efficiently and minimize losses resulting from suboptimal decisions (Abyad, 2020).

Failure Mode refers to the mechanism by which a system, subsystem, or component fails to operate. It is used to describe how a piece of equipment or system can malfunction, including the type of failure that occurs and its impact on the overall system (Martiniello et al., 2020). Failure Mode encapsulates the various mechanisms through which systems, subsystems, or components may fail to function as intended. It serves as a critical concept in understanding the nature of malfunctions across equipment and systems, clarifying the types of failures that may ensue and their subsequent impacts on overall system performance (Emerson et al., 2024)(Antomarioni et al., 2020). In the power plant sector, particularly at power plant, Failure Mode is applied to identify potential failures and mitigate risks that may arise and affect the system potentially leading to plant downtime or operational failure (Bhangu et al., 2011a)(Bhangu et al., 2011b). Moreover, understanding Failure Modes is essential for enhancing reliability and improving operational strategies within power plant facilities. It fosters exploration of different interfaces and integration points within the system, contributing to better risk management practices and heightened dependability of operational systems (Wu, Wang, et al., 2021)(Aschidamini et al., 2022). By employing FMEA, organizations can scrutinize various design alternatives that not only minimize failure risks but also optimize the cost-effectiveness of their operations, ultimately ensuring sustained productivity and operational stability (Zheng et al., 2021)(Patil et al., 2022).

Life Cycle Management is also a crucial approach in asset management within the energy sector. LCM focuses on the sustainable management of assets throughout their entire life cycle from the planning stage to decommissioning (Widya et al., 2024). This approach aims to ensure that investments deliver maximum value throughout their operational lifespan, while also reducing the risk of incurring additional future costs. By applying LCM, companies can optimize resource utilization, enhance operational efficiency, and support environmental sustainability (Rigamonti & Mancini, 2021). In addition, the evolving framework of LCM includes considerations for economic factors, as noted in the work of Paliwoda et al., which highlights how increasing environmental awareness among stakeholders influences purchasing decisions (Paliwoda et al., 2024). This reference is suitable, but its application to asset management strategies in the energy sector should be clarified. Recent insights indicate a growing emphasis on integrated decision-making approaches that foster responsible investment in sustainable energy technologies. However, the Almoudi study is incorrectly cited, as the reference provided discusses tax incentives rather than comprehensive frameworks for sustainable energy technologies. Therefore, this citation is removed to prevent misrepresentation.

Integrating the concepts of Pareto Loss and Life Cycle Management at power plant can serve as an effective strategy to address various existing challenges. In this context, Pareto Loss can be applied to identify the key factors that most significantly influence investment success, such as technical risks, operational costs, or regulatory impacts (Fettah et al., 2024). Meanwhile, can be used to ensure that power plant assets are managed efficiently throughout their life cycle (Rooscote et al., 2023). The combination of these two approaches provides a comprehensive framework for investment management in the energy sector. Integrating Pareto Loss and Life Cycle Management at power plant represents a strategic approach to effectively tackle various operational and financial challenges within the energy sector. The application of Pareto Loss facilitates the identification of pivotal factors that substantially impact investment outcomes, particularly in terms of technical risks, operational costs, and regulatory compliance (González-Muñoz et al., 2024)(Al-Obaidli et al., 2023).This analytical technique emphasizes focusing on the critical few elements, thereby optimizing resource allocation and risk management strategies, which are vital for enhancing investment success (Scarpellini et al., 2021). Concurrently, Life Cycle Management offers a systematic framework for overseeing power plant assets throughout their entire lifecycle, ensuring that strategic decisions accommodate not only immediate operational needs but also long-term sustainability goals (Khudyakova et al., 2020). The synergy of these two methodologies affords a comprehensive investment management framework that is capable of addressing both current challenges and anticipating future shifts in the energy landscape (Papadopoulos et al., 2023a). The combined strategy allows for a dual focus that maximizes operational efficiency while minimizing financial exposure. For instance, incorporating insights from Pareto analysis may guide investments in measures that yield the most significant impact on performance metrics, while LCM ensures that the lifecycle costs and benefits are meticulously accounted for in the investment decisions (Scarpellini et al., 2021).

Application of Pareto Loss**,** Failure Mode and Life Cycle Management concepts is expected to provide both practical and strategic solutions for investment management at power plant. By adopting a systematic approach, energy companies can adapt to dynamic business environments while contributing positively to the sustainable development of power plant. Moving forward, the implementation of Pareto Loss, Failure Mode, and LCM can serve as a strategic step to enhance competitiveness and long-term business sustainability (Haievskyi, 2020). Through optimized investment decision-making, the company can not only achieve efficiency and profitability but also ensure long-term operational continuity. This approach positions power plant as a potential model for innovative and sustainable investment management in the energy sector. The implementation of concepts such as Pareto Loss, Failure Mode, and Life Cycle Management (LCM) within the context of investment management at power plant can yield substantial practical and strategic benefits. A systematic approach incorporating these concepts allows energy companies to navigate the complexities of evolving business landscapes while contributing to the sustainable development of infrastructures like power plant. Studies highlight that a structured analysis and management of investment practices, aligned with sustainability paradigms, enhance both operational efficiency and financial viability in the energy sector (Olave-Rojas & Álvarez-Miranda, 2021). Through the integration of advanced methodologies for failure mode and effect analysis (FMEA), organizations can develop risk management strategies essential for sustaining operations in turbulent market conditions (Rehman et al., 2020).

Conclusion the adoption of Pareto Loss, Failure Mode Analysis, and LCM represents a forward-thinking movement toward a more sustainable energy sector. These methodologies allow power plant to fine-tune its investment strategies for enhanced economic returns while contributing meaningfully to environmental sustainability and societal welfare (Su & Sun, 2023). This approach underscores the vital role of strategic investment management in fostering long-term sustainability within the energy domain, reinforcing the potential of power plant as a benchmark for future initiatives in sustainable energy investment management (Alsayegh et al., 2022).

Previous studies have explored various risk management methods such as Bow-Tie, BIA, FMEA, and the Cornish-Fisher expansion in the energy and manufacturing sectors, particularly within Indonesia's power plants and during the COVID-19 crisis. However, further research is still needed to evaluate the effectiveness of these methods when applied across different industries or under diverse economic scenarios. Furthermore, the application of Pareto optimality in decision-making and recent analyses have been conducted to explore the link between Life Cycle Assessment (LCA) and circularity indicators. Risk management based on Life Cycle Management (LCM) is a strategic approach whereby companies monitor assets and associated risks to generate actions that impact corporate goals before prioritizing investments. This aims to extend asset lifespan and reduce asset-related risks. This opens up opportunities for more detailed research to reinforce and broaden the practical application of these methods in supporting greater operational efficiency and sustainability (Anysz et al., 2020) (Dedy et al., 2018) (Mahendra, 2024) (Lo Presti et al., 2024) (Sapruwan et al., 2024) (Rigamonti & Mancini, 2021) (Rooscote et al., 2023).

Furthermore, the concept of Pareto optimality has been increasingly integrated into decision-making frameworks, particularly in conjunction with Life Cycle Assessment (LCA) and associated circularity indicators (Paliwoda et al., 2024). This synthesis of methodologies allows organizations to evaluate the environmental impacts of their practices, thereby promoting sustainability. Life Cycle Management (LCM) serves as a strategic approach by which firms optimize asset monitoring and risk assessment to influence corporate objectives effectively (Olave-Rojas & Álvarez-Miranda, 2021). By focusing on extending the lifespan of assets and minimizing associated risks, LCM promotes superior sustainability outcomes. Moreover, the potential for additional research in this region remains vast, offering avenues for enhancing operational efficiency and achieving sustainability targets within various industrial applications (Paliwoda et al., 2024).

Unlike previous studies, this research focuses on investment management in the energy sector through the integration of Pareto Loss, Failure Mode, and Life Cycle Management (LCM) concepts, using a case study of power plant in South Kalimantan. The study emphasizes strategic investment decision-making to ensure operational efficiency and long-term sustainability. Through a data-driven approach, this research fills a gap in the literature by applying the principles of Pareto, Failure Mode, and LCM within the energy sector context an area that has not been extensively explored in prior research.

This research contributes to the field of investment management in the energy sector by integrating Pareto Loss, Failure Mode, and Life Cycle Management (LCM) principles into a comprehensive framework, focusing on the specific case of power plant in South Kalimantan. While previous studies have addressed aspects of investment within renewable energy, this analysis emphasizes a structured approach to strategic decision-making aiming at enhancing operational efficiency and long-term sustainability in energy investments (Gotoh et al., 2022) (Konstas et al., 2023a). The application of methodologies such as real options analysis provides potential pathways for investment decisions under uncertainty, presenting a perspective that has received limited attention in the existing literature (Dobrowolski & Drozdowski, 2022) (Locatelli et al., 2020). Further, this research employs a data-driven approach, addressing gaps found in earlier explorations of investment strategies in the energy domain. By integrating concepts from Pareto analysis, Failure Mode Effect Analysis (FMEA), and LCM, the work enriches the discourse surrounding energy sector investment frameworks and offers stakeholders insights into optimizing resource allocation and mitigating risks elements that have often been underappreciated in prior study (Arku et al., 2024), the case study of power plant serves a dual purpose: it validates these theoretical contributions and highlights the necessity of adopting a multidimensional perspective in energy investment research aimed at ensuring sustainability (Aldossary et al., 2022). In conclusion, the integration of LCM, Pareto, and FMEA within investment management distinctly positions this study as an innovative effort to redefine strategic decision-making in the energy sector, offering implications for future research and practical applications (Papadopoulos et al., 2023b).

The purpose of this research is to identify the key factors that influence investment success in the energy sector, particularly at power plant. The approach involves integrating the concepts of Pareto Loss, Failure Mode, and Life Cycle Management (LCM) as a data-driven investment management strategy focused on efficiency, sustainability, and long-term value. By leveraging data-based approaches such as Pareto Loss, Failure Mode, and Life Cycle Management, companies in the energy sector including power plant can enhance their competitiveness, efficiency, and business sustainability. This study is expected to make a significant contribution by helping companies make better investment decisions while promoting the development of a more sustainable energy sector in Indonesia.Utilizing data-centric frameworks encourages energy companies to adopt innovative investment strategies that align with market demands and sustainability goals. By integrating Failure Mode Effects Analysis and Life Cycle Maintenance, organizations can better identify risks and opportunities throughout the investment lifecycle. This synergizes timely decision-making that fosters long-term viability and growth in the energy sector, particularly given current global shifts toward renewable resources and sustainable energy practices (Rocha-Meneses et al., 2023). Implementing these methodologies is anticipated to provide substantial contributions to the strategic investment planning process, facilitating improved decision-making that supports the development of a more robust and sustainable energy sector in Indonesia (Alsayegh et al., 2022).

2 Methods

This study employs a Concurrent Mixed Methods approach by simultaneously integrating quantitative and qualitative methods to analyze the application of the Pareto Loss, Failure Mode and Life Cycle Management concepts in improving investment decision-making efficiency at power plant (Yoshida et al., 2019). The objective is to assess and analyze the relationship between key investment factors and asset life cycle management with the efficiency of decision-making, evaluated concurrently. The research utilizes primary data obtained through interviews with expert informants and secondary data sourced from company documents (Ahmed et al., 2020). These documents include Pareto Loss data, Failure Mode data, and Operational Efficiency Reports from the power plant.

3 The current study adopts a Concurrent Mixed Methods approach, integrating quantitative and qualitative methodologies to investigate the application of Pareto Loss, Failure Mode, and Life Cycle Management (LCM) principles aimed at enhancing investment decision-making efficiency at power plant. The primary aim is to assess the interplay between critical investment variables and asset life cycle management on decision-making efficacy, evaluated simultaneously. This approach aligns with methodologies suggested in previous research that emphasizes the need for robust decision-making frameworks in energy sectors, particularly in the context of managing complexities in investment dynamics (Konstas et al., 2023b).

7 Data collection comprises both primary and secondary sources; primary data is gathered through expert interviews, while secondary data includes corporate documentation relevant to Pareto Loss, Failure Mode analysis, and Operational Efficiency Reports from the power plant. The use of qualitative methods to validate findings through expert insights corresponds with established practices in decision-making literature, asserting that qualitative data can significantly enhance the richness and reliability of analyses in complex domains. Furthermore, Failure Modes and Effects Analysis (FMEA) plays a vital role in evaluating operational reliability, thus contributing substantively to the assessment of various investment decision to gather insights from the Unit Manager and the involved Assistant Managers from engineering, maintenance, and operations departments.

The methodology employed in this research aligns with established frameworks in decision-making within energy sectors, particularly outcomes (Wang et al., 2022). Utilizing comprehensive datasets reinforces the investigation's validity and aligns with best practices for systematic asset management By concurrently applying qualitative and quantitative assessments, the study aims not only to improve investment decision-making efficiency but also to facilitate a nuanced understanding of the factors influencing long-term sustainability and effectiveness within the energy sector. Overall, this research builds upon existing frameworks that highlight the importance of integrating diverse methodologies to inform strategic decisions in complex operational landscapes (Tran et al., 2023).

The data collection techniques used in this study include the gathering of Pareto Loss data**,** Failure Mode data which identifies failure modes within the system and Life Cycle Management data as the initial basis for investment proposals(Wu, Liu, et al., 2021). A Focus Group Discussion was conducted to examine Failure Modes with the Assistant Manager of Engineering**,** Assistant Manager of Maintenance**,** Assistant Manager of Operations**,**Unit Manager**.** In addition**,** questionnaires were distributed to support investment decision-making, involving the Unit Manager**,** Assistant Manager of Engineering**,** Assistant Manager of Maintenance and Assistant Manager of Operations**.**

In this study, data collection was undertaken through various methods, including the compilation of Pareto Loss data, Failure Mode data to identify dysfunctions within the operational system, and Life Cycle Management (LCM) data to form the foundational basis for investment recommendations. To facilitate a comprehensive analysis of the identified Failure Modes, Focus Group Discussions (FGDs) were conducted involving key personnel, such as the Assistant Manager of Engineering, Assistant Manager of Maintenance, Assistant Manager of Operations, and Team Leaders from both Maintenance and Operations domains. Furthermore, to support the investment decision-making process, questionnaires were distributed concerning the understanding of various failure modes and their implications on operational efficiency and investment potentials. Specifically, the utilization of FGDs as a primary qualitative data collection method is supported by research that advocates for collaborative discussions among key stakeholders to enhance understanding of operational challenges and facilitate targeted investments (Rosłon et al., 2020). The deployment of questionnaires further enhances the data richness available for analysis, facilitating a broader perspective on the investment decision-making process from management-level personnel, which has been highlighted in previous studies emphasizing the importance of multi-faceted input in strategic planning (Borodin et al., 2021). Additionally, the integration of LCM data within the investment assessment framework is particularly critical, as past studies affirm that effective life cycle costing optimizes financial resource allocation and improves long-term investment outcomes (Ruiz-Fuensanta et al., 2019). Such comprehensive data collection methods are pivotal, especially in contexts marked by uncertainty and the need for robust decision-making frameworks that can dynamically adapt to changing operational landscapes (Cheng et al., 2021).

The initial phase of this research involved conducting a Pareto loss analysis**,** focusing on identifying the major contributors to failure at power plant during the period from January to December 2024. The Failure Mode analysis explored the failure mechanisms within the system, while the Life Cycle Management (LCM) analysis examined the basis for investment decision-making grounded in Pareto loss, failure mode, and asset lifecycle considerations (Vyas et al., 2017). This methodology was designed to ensure that all relevant aspects influencing the success of investments at power plant are thoroughly identified and analyzed, and subsequently illustrated in a flowchart**.**

The next phase of this research involved the use of triangulation to verify the accuracy of the collected data. This approach integrates various data sources and methods to ensure the validity of findings and enable data processing. Source triangulation drew from two types of sources: direct interviews with experts at power plant and official company documents. This method offers both field-level insights and a broader understanding of the written data. Time triangulation was carried out by observing data over a specific period January to December 2024 with control points taken in the morning, afternoon, and evening. This ensured daily accuracy and monthly validation to capture trends and changes occurring over time. This was crucial for assessing the effectiveness of implemented policies and observing how conditions evolved.Method triangulation integrated both qualitative and quantitative analyses. This included calculating losses using Pareto analysis, evaluating failures through focus group discussions, and applying life cycle management to assess investment decisions. The combination of methods moved beyond numeric data to provide deeper insights into how decisions were made and implemented in real-world contexts.By integrating these approaches, the research aims to deliver a comprehensive and in-depth analysis that not only presents data but also its context and implications enabling power plant to make more informed and strategic investment decisions for the future.

3 Results

Based on the Top Ten Pareto analysis, the primary component contributing to performance degradation of the power plant unit is the turbine blade. The blade turbine plays a crucial role in the power plant as a driver of the turbine rotor, efficiently converting thermal energy into kinetic energy. Anomalies in the blade turbine result in excessive vibration and potential mechanical failure, which subsequently cause operational derating and reduced efficiency (↑NPHR, ↓Efficiency). This finding is further supported by Failure Mode Analysis, which identifies several failure modes in the blade turbine, including: Mech-Looseness, Mech-Deformation, Mech-Leakage, Mech-General, and Mech-Clearance/Alignment, all of which registered high risk scores. The most significant failure mode is Mech-Looseness, which leads to rotor imbalance and severe vibrations, followed by Mech-Deformation due to high temperatures, operating pressure, and blade lifetime fatigue.

Turbine failure modes identifies five critical failure types with maximum risk scores (100), indicating urgent conditions that demand immediate action. The top priority is Mech-Looseness, as component imbalance can cause excessive vibrations leading to total shaft failure. The second is Mech-Deformation, where blade warping due to thermal creep or overload significantly reduces energy conversion efficiency. Next is Mech-Leakage, typically resulting from poor sealing, which lowers thermal efficiency and poses safety risks. Fourth is Mech-Clearance/Alignment, where improper installation leads to friction and localized heating, accelerating wear. Lastly, Mech-General refers to overall material fatigue, emphasizing the need for regular maintenance and monitoring.

The emergency blade trimming was triggered by a combination of critical factors: operational conditions such as excessive steam pressure beyond the limit and unstable load control; inconsistent maintenance practices that failed to detect early damage; poor material quality due to manufacturing defects and thermal fatigue; and environmental factors such as high humidity and extreme temperatures that accelerated corrosion and material degradation. While this measure was effective as a temporary mitigation to prevent further damage, it must be promptly followed by a comprehensive technical audit, enhancement of predictive maintenance programs, regular inspections, and technician training to ensure a sustainable long-term solution to turbine issues.

The pattern clearly shows a sharp spike on March 2, 2024, with the total derating duration approaching 700 hours, marking the peak derating incident during the observation period. Additionally, there were several other significant spikes on February 16, April 1, and April 15, each recording derating durations exceeding 200 hours, indicating that blade damage-related disruptions occurred frequently and repeatedly. The 151-hour derating caused by blade damage is directly classified as equivalent forced derated hours, which is a key component in calculating EFOR. The recorded EFOR of 1.76% for the year 2024 reflects that approximately 1.76% of the Total operational time experienced partial outages due to technical conditions. The derating chart serves as a visual representation of EFOR the higher and more frequent the derating, the greater the EFOR value, indicating lower unit reliability in operational performance. An EAF of 1.72 (on a ratio scale or 98.28% in percentage terms) indicates that the unit remains relatively available for operation, though with a reduction in availability due to derating. Prolonged derating, when accumulated overtime, will gradually erode the unit's actual availability.

$$\boldsymbol{EFOR = \frac{FOH + EFDH}{FOH + SH + EFDHRS}\ X\ 100\%} \qquad \boldsymbol{EAF = \frac{POH - FOH - EFDH - EFDHRS}{POH}\ X\ 100\%} \qquad \textbf{(1)}$$

1.75 % **98.25 %**

Formula:

EFOR is calculated based on the total Equivalent Forced Derated Hours (EFDH) in relation to the total operational hours. According to the data provided:

- FOH (Forced Outage Hours) = 0 hours
- EFDH (Equivalent Forced Derated Hours) = 151 hourr
- SH (Service Hours) = 8,609 hours
- EFDHRS (Equivalent Forced Derated Hourly Rate) = 0 hours
- POH (Planned Outage Hours) = 8,609 hours
- FOH = 0 hours
- EFDH = 151 hours

- EFDHRS = 0 hours

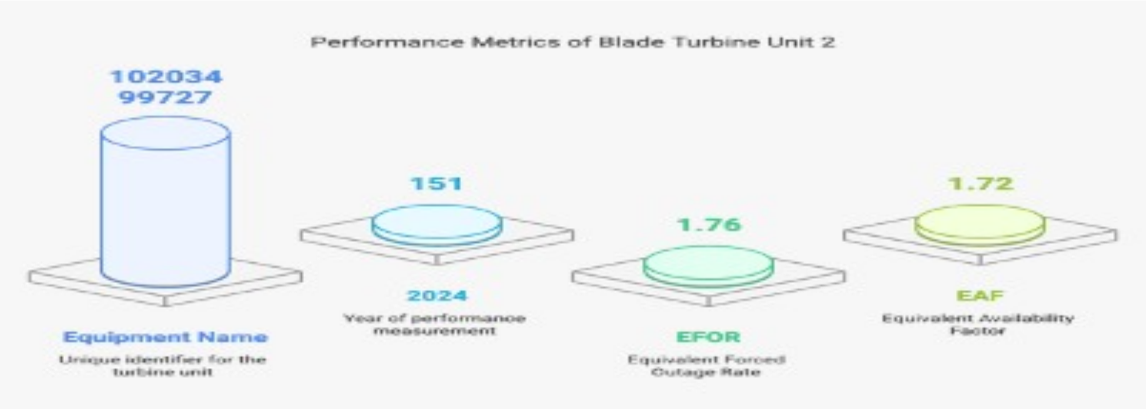

Figure 1. Diagram of Blade Turbine Unit 2 Efficiency

The performance of the Unit 2 turbine blade in 2024 from figure 1, recorded an Equivalent Availability Factor (EAF) of 1.72 (on a specific ratio scale) and an Equivalent Forced Outage Rate (EFOR) of 1.76%. A total of 151 hours of partial outages (derating) occurred during the operational period, indicating a reduced ability of the unit to reach its optimal power output. The low EAF value signifies that the turbine frequently experienced partial disruptions, leading to diminished energy production capacity. Meanwhile, the EFOR value of 1.76% confirms that a portion of the operational time was compromised, particularly due to issues with the turbine blades. Consequently, these findings highlight the urgent need for the power plant to improve operational reliability through predictive maintenance strategies and targeted investment in the components especially the turbine blades t of critical components especially the turbine blades.

Figure 2. Blade Turbine Investment Projection

The investment analysis in figure 2, shows that the Rp5,955,150,000 investment demonstrates strong financial feasibility, with potential annual savings reaching Rp9,791,568,000. Key financial indicators reflect excellent investment performance: a Net Present Value (NPV) of Rp54,966,699,091.46, an Internal Rate of Return (IRR) of 164%, a very short Payback Period (PP) of just 1 year, and a remarkably high Benefit-Cost (B/C) ratio of 16.44. These figures confirm that the investment is not only financially viable but also highly profitable and carries low risk in the face of economic uncertainty over the next 10 years.As a result, there is a strong recommendation to proceed with this investment as a strategic decision for the company. The study also reveals that the projected Net Present Value growth trend over 10 years is consistently positive for the Blade Turbine investment. The NPV becomes positive in the first year, reaching Rp296 million, indicating that the investment begins delivering economic benefits quickly. A significant increase is observed in year three, with the NPV reaching Rp888 million, signifying effective capital recovery. By year five, the NPV reaches Rp1.283 billion, confirming that the initial investment has been fully recovered through operational efficiency and reduced turbine derating. It clearly demonstrates that the investment will enhance both technical efficiency and profitability for power plant.

Table 1. **Net Present Value, Internal Rate Return, Payback Pheriod and Beneffit Cost**

Parameter	Value	Interpretation
Net Present Value	Rp54.966.699.091	A highly positive NPV indicates the project generates significant added value.
Internal Rate of Return	164%	IRR is far above the discount rate, making the investment highly feasible.
Payback Period	1 Year	PP of only 1 year indicates a very fast return on investment.
Benefit-Cost Ratio	16,44 Times	Every Rp1 invested yields Rp16.44 in benefits, indicating excellent efficiency.

Presents the financial analysis results of the Blade Turbine replacement investment project at Power Plant, indicating that the project is highly feasible (Table 1). The Net Present Value (NPV) of Rp54.97 billion reflects a significant net profit over a 10-year period. The Internal Rate of Return (IRR) reaches 164%, far exceeding the discount rate of 9.71%, signaling a very high investment return. The Payback Period (PP) is only 1 year, reflecting rapid capital recovery and minimal liquidity risk. Meanwhile, the Benefit-Cost Ratio (B/C) of 16.44 indicates that every Rp1 invested generates Rp16.44 in benefits, demonstrating exceptional financial efficiency. These findings reinforce that the project is highly profitable both technically and and economically.

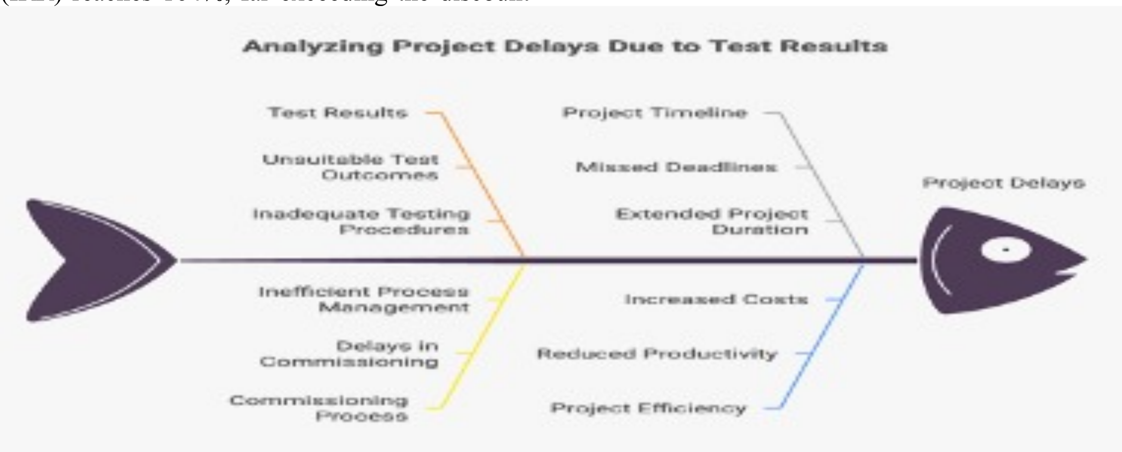

Figure 3. Fishbone Matrix Risk Investment

Fishbone diagram in Figure 3, illustrates the primary sources of risk in the blade turbine investment at Power Plant. The highest risks are concentrated in four areas : planning, execution, procurement, and testing/commissioning. During the planning phase, design errors and insufficient reviews lead to blade specifications that do not match field conditions. The execution stage faces risks such as project delays and logistical constraints, which impact the shutdown schedule. On the procurement side, weak contract clauses and limited vendor options increase the risk of poor quality. Meanwhile, the testing and commissioning phase is vulnerable to performance test failures and delays in restarting operations. This comprehensive analysis highlights that blade investments are highly vulnerable without cross-functional mitigation. Therefore, a combined application of Life Cycle Management (LCM), Pareto Loss, and Failure Mode Analysis is essential to maintain plant reliability and efficiency.

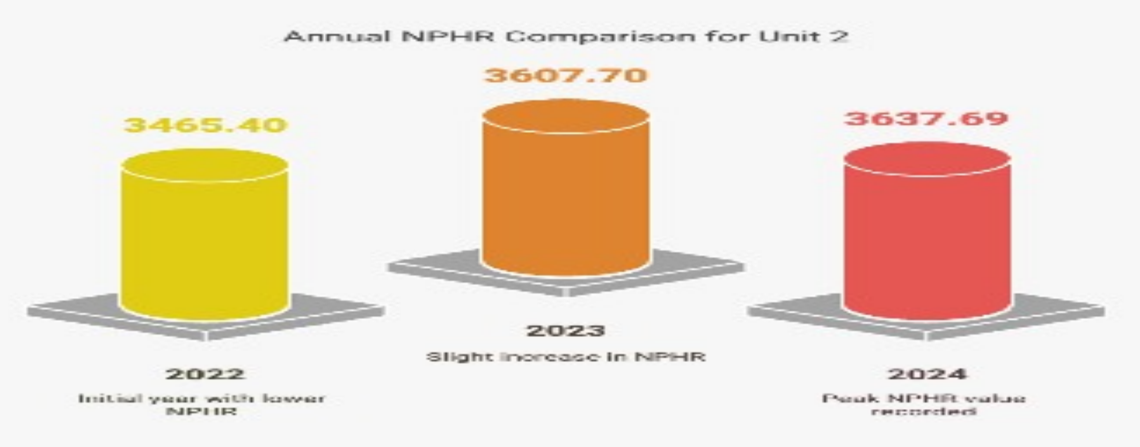

Figure 4. NPHR Graph of Blade Turbine Unit 2

Research findings indicate that the NPHR (Net Plant Heat Rate) graph for Unit 2 during the 2022–2024 period from figure 4, shows a clear increase from 3465.40 kCal/kWh in 2022 to 3637.69 kCal/kWh in 2024. This rise of 172.29 kCal/kWh reflects a significant decline in thermal efficiency, meaning more heat energy is required to produce each kilowatt-hour of electricity. This negative trend suggests potential operational issues, such as turbine blade degradation, poor combustion quality, or external factors like declining fuel quality.From a risk perspective, this increase in NPHR will lead to higher fuel costs and greater environmental impact due to increased carbon emissions, reducing company profitability (as reflected in ROA and ROE) and increasing operational risks. Furthermore, NPHR data plays a critical role within the Enterprise Risk Management (ERM) framework, serving as a basis for risk evaluation, overhaul scheduling, and long-term investment strategies aimed at sustaining optimal operational performance.

4 Discussion

The research framework is built upon the relationship between power plant operational performance, critical component risks, and data-driven investment decision-making strategies (Figure 5). The starting point of this framework is the identification of major losses using Pareto Loss Analysis, which highlights that the most significant derating disruptions stem from damage to Blade Turbine Row 14. This is followed by a Failure Mode Analysis, revealing that *Mech-Looseness* and *Mech-Deformation* are the dominant causes of performance decline, leading to an increase in Equivalent Forced Outage Rate (EFOR) and a decrease in Equivalent Availability Factor (EAF), as well as thermal efficiency (Net Plant Heat Rate). The next step in this framework is the implementation of Life Cycle Management (LCM) as a strategic approach to map the technical lifespan of assets and determine the optimal timing for investment. LCM is used to integrate technical findings with financial feasibility analysis through parameters such as Net Present Value (NPV), Internal Rate of Return (IRR), Payback Period (PP), and Benefit/Cost Ratio (B/C). This approach enables a comprehensive assessment from both technical and economic perspectives.To enhance decision validity, the framework is supported by a triangulation method combining quantitative data (EAF, EFOR, NPHR, NPV, IRR) and qualitative data (expert interviews, field observations, FGDs) while also considering time and source dimensions. The outcome of this framework is not merely a numeric investment conclusion, but also a long-term risk mitigation strategy, such as predictive maintenance, improved inspection quality, and enhanced technician capabilities. Thus, the framework provides a systematic path from identifying dominant risks, diagnosing root technical causes, mapping asset life cycles, to evaluating investment feasibility ultimately impacting the efficiency, reliability, and sustainability of power plant operations.

Figure 5. Frame Work Investment Execution Flow Chart

Table 2. Interconnections between Pareto Loss, Failure Mode, and Life Cycle Management from Technical Side

Component	Technical Function	Technical Linkages
Pareto Loss Analysis	Identify the most impactful sources of operational loss (e.g., derating from Blade Turbine Row 14).	Provides prioritization for high-loss events; directly correlates with efficiency indicators like EAF, EFOR, and NPHR.
Failure Mode Analysis	Diagnose root causes of technical failures (e.g., Mech-Looseness, Deformation).	Explains the mechanical causes behind operational inefficiencies; connects to higher EFOR, lower EAF, and increased NPHR.
Life Cycle Management (LCM)	Manage the asset's lifecycle to determine optimal investment timing and performance tracking.	Integrates data from Pareto and Failure Mode to evaluate technical performance and justify financial metrics like NPV, IRR, and PP.

Pareto Loss provides a macro-level diagnosis of performance losses, identifying the most impactful sources of operational inefficiency (Table 2). This diagnosis is further refined through Failure Mode Analysis (FMA), which breaks down the technical root causes behind the losses, such as mechanical looseness or deformation. Life Cycle Management (LCM) then integrates both the macro (Pareto) and micro (FMA) insights to formulate a comprehensive strategy for technical and financial investment decisions.

Without Pareto Loss, technical efforts risk being misdirected due to a lack of prioritization. Without FMA, the specific technical issues cannot be accurately addressed or mitigated. And without LCM, the timing and value of component replacement such as turbine blades lack a structured, data-driven foundation. Together, these approaches ensure that investment decisions are both technically justified and strategically aligned with asset performance goals.

About The findings of this research are firmly aligned with the structured stages of the Investment Execution Flowchart (Enhanced 8-Step Version)**,** demonstrating a comprehensive, data-driven decision-making approach to asset investment in power plant. Beginning with the Pareto Loss Analysis**,** the identification of Blade Turbine Row 14 as the dominant contributor to operational derating (with cumulative disturbances exceeding 700 hours) was pivotal.

This finding narrowed the focus onto the component with the highest economic and technical impact.Subsequently, the application of Failure Mode Analysis revealed that Mech-Looseness and Mech-Deformation were the critical root causes of turbine inefficiencies. These failure modes directly contributed to elevated vibration levels and partial shutdowns.

5 Conclussions

This study concludes that the implementation of Life Cycle Management (LCM), when combined with the Pareto Loss and Failure Mode Analysis approaches, has proven effective in enhancing the accuracy of investment decisions regarding Blade Turbine Row 14 at POWER PLANT. Key findings reveal that disturbances categorized as Mech-Looseness and Deformation are the dominant causes of derating, with total downtime exceeding 700 hours, leading to a decline in thermal efficiency and an increase in NPHR to 3637.69 kCal/kWh in 2024. From a financial standpoint, the investment of IDR 5.95 billion is deemed highly feasible, supported by an NPV calculation of IDR 54.97 billion, an IRR of 164%, a Payback Period of only 1 year, and a Benefit/Cost Ratio of 16.44 times. This research offers a strategic contribution to investment decision-making by presenting an integrative model based on actual data and operational context. However, the study is limited by its single-site scope and one-year observation period, and it does not yet consider the influence of external factors such as market dynamics or national energy policies. Therefore, future research is recommended to include a broader range of power units, extend the evaluation period, and integrate digital technologies such as real-time monitoring and predictive analytics to generate more precise and adaptive investment decisions.

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