

Research Article

## Optimizing CAPEX and OPEX through Predictive AI Strategies Aligned with ISO 55010 for Improved Maintenance Cost Accuracy

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**Abstract:** Ensuring accurate maintenance budgeting is a critical requirement for sustaining operational reliability in coal-fired power plants, particularly in facilities operating under strict fiscal constraints. At the Palabuhanratu Coal-Fired Power Plant (CFPP), the main challenge addressed in this study is the persistent maintenance budget deviation of up to 30%, driven by reliance on reactive planning and the absence of predictive cost estimation tools. This misalignment between financial planning and asset performance has resulted in inefficient resource allocation, cost overruns, and unplanned downtime. To overcome this, the study aims to develop and implement a predictive artificial intelligence (AI)-driven cost management system, aligned with ISO 55010 principles, optimizing capital expenditure (CAPEX) and operational expenditure (OPEX) allocation while improving maintenance cost accuracy. The methodology integrates multivariate regression modelling and reliability analysis using Python, trained on three years of historical operational data from Enterprise Resource Planning (ERP) and Computerized Maintenance Management System (CMMS) platforms. The system is deployed via an interactive Looker Studio dashboard that enables real-time monitoring and cross-functional alignment between finance and engineering. Implementation results show a reduction in maintenance costs from USD 144,000 to USD 41,867, a decrease in MWh loss from 72.7 GWh to 43.1 GWh, and total annual savings of USD 2.19 million. The findings demonstrate that predictive AI, when integrated with ISO 55010-based asset management, can significantly enhance cost efficiency, operational reliability, and budgetary precision. This approach not only addresses critical challenges in maintenance cost management but also provides a replicable framework for other power plants, supporting broader adoption of data-driven asset optimization practices in the energy industry.

**Keywords:** asset management, predictive maintenance, AI, ISO 55010, maintenance cost optimization, CAPEX, OPEX, power plant reliability

### 1. Introduction

The global power sector is undergoing rapid transformation, driven by increasing electricity demand, aging infrastructure, and the pressing need to achieve both cost efficiency and environmental sustainability. According to the International Energy Agency (IEA), global electricity demand is projected to grow by over 3% annually through 2030, with developing economies accounting for nearly 90% of this increase [1]. In Indonesia, coal-fired power plants (CFPPs) remain the backbone of baseload electricity supply, contributing more than 60% of total generation capacity [2].

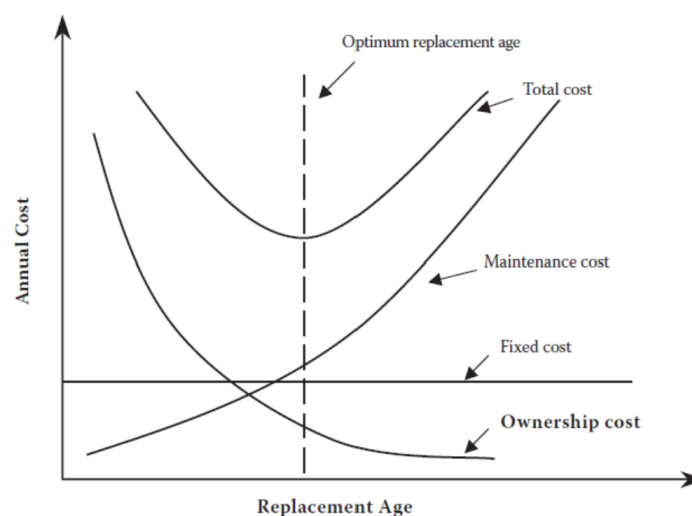
Ensuring the operational reliability of these plants under constrained budgets has therefore become a strategic necessity. The Palabuhanratu CFPP, a  $3 \times 350$  MW facility and a critical asset in the Java–Bali power grid, exemplifies these operational and financial challenges.

The main problem addressed is the persistent maintenance budget deviation of up to 30% at Palabuhanratu CFPP, caused by reliance on reactive maintenance planning and trend-based forecasting without predictive cost estimation tools [3]. This misalignment between financial planning and asset performance results in inefficient resource allocation, cost overruns, and an elevated risk of unplanned downtime, and increasing opportunity losses.

Existing research has extensively demonstrated the benefits of predictive maintenance in industrial asset management. Zonta et al. [4] and McKinsey & Company [5] report that predictive analytics can enhance asset performance and reduce unplanned outages by accurately forecasting equipment failures. More recent studies [6], [7] have extended predictive maintenance into integrated decision-support systems; however, their scope largely remains within failure prediction and short-term operational decision-making. Direct integration of these predictive insights into strategic financial planning—particularly for optimizing capital expenditure (CAPEX) and operational expenditure (OPEX)—is still underexplored. Furthermore, ISO 55010, which emphasizes the alignment of financial and non-financial asset management functions, has seen minimal practical implementation in power generation cost optimization [8].

This study aims to develop and implement a predictive artificial intelligence (AI)-driven cost management system aligned with ISO 55010 to optimize CAPEX and OPEX allocation while improving maintenance cost accuracy. The methodology uses three years of historical operational and financial data, combining multivariate regression modelling with reliability analysis, and deploying a real-time interactive dashboard. Target outcomes include reducing budget deviations and improving cost forecasting accuracy.

To illustrate cost optimization, Figure 1 shows the relationship between asset age and total cost [9]. As assets age, maintenance costs increase due to more frequent and complex repairs, while fixed costs remain stable. The optimal replacement age—the point of minimum total cost—marks when replacing assets yields maximum savings and performance benefits, helping avoid excessive costs and maintain operational reliability.



**Figure 1.** Optimal Replacement Age Based on Cost Analysis [9].

## **2. Materials and methods**

The development and implementation of the Optimization of CAPEX and OPEX Management through Predictive AI and Intelligent Strategy was carried out through six structured and comprehensive systematic stages. This methodological approach was designed to ensure the successful development of an AI-based cost management system aligned with ISO 55010 at Palabuhanratu CFPP.

### **2.1. Problem Identification**

Effective maintenance cost management is vital to sustaining operational reliability and financial performance in coal-fired power plants. At Palabuhanratu CFPP, recurring deviations between planned and actual maintenance expenditures ranging from 20% to 30% signal fundamental inefficiencies in budgeting practices [3]. These inefficiencies stem from reactive maintenance planning, limited use of historical failure data, and the absence of predictive cost estimation tools.

To address this, a structured gap analysis was conducted by comparing existing CAPEX and OPEX management workflows against ISO 55010:2019. The assessment revealed critical misalignments between financial planning and asset performance priorities, particularly in how maintenance activities are justified and resourced. The lack of integration between technical and financial functions was identified as a key contributor to budgetary inaccuracy.

Root cause diagnosis was supported by the 5-Why method to categorize inefficiency drivers across technical, procedural, and organizational domains. Pareto Analysis further confirmed that a small number of high-risk assets were responsible for most unplanned costs and downtime.

### **2.2. Data Collection Techniques**

Data collection focused on obtaining comprehensive inputs to support predictive maintenance modelling and cost forecasting. Historical CAPEX and OPEX data from the past three years were gathered, including expenditure records, maintenance logs, failure frequencies, and downtime durations. These were sourced from Enterprise Resource Planning (ERP), and Computerized Maintenance Management System (CMMS-IBM Maximo) systems.

Direct field observations and audits of maintenance workflows were conducted to identify reactive planning patterns and resource inefficiencies. Additionally, operational parameters such as Mean Time Between Failure (MTBF), Mean Time to Repair (MTTR), and MWh Loss were extracted to quantify equipment reliability.

All datasets were cleaned and structured for machine learning input, serving as the foundation for root cause analysis, reliability modelling, and cost prediction. This multi-source approach ensured both technical and financial dimensions were well-represented in system development.

### **2.3. Planning and Analysis**

The planning and analysis phase forms the foundation for developing a predictive cost management system that is both technically robust and strategically aligned. This stage is critical for addressing key issues such as budget deviations, unexpected maintenance expenses, and inefficiencies in asset lifecycle management—factors that can threaten overall system reliability and performance.

During this phase, reliability analysis plays a pivotal role by enabling a data-driven understanding of asset degradation trends and failure behaviours. To model equipment failure patterns accurately, a statistical distribution approach is utilized, where distributions such as Weibull, Exponential, Lognormal, and Normal are applied. Each distribution offers unique characteristics in

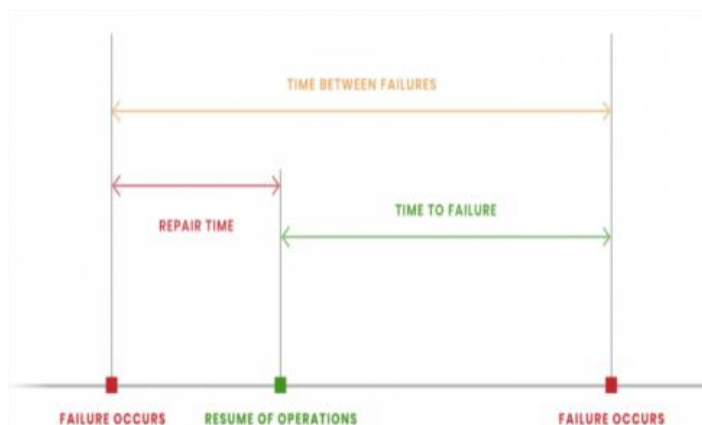
capturing time-to-failure behaviour, hazard rates, and system reliability over time, making them highly suitable for different types of equipment and operational contexts [10].

To enhance accuracy and objectivity, a machine learning-based model was developed using Python (Jupyter Notebook 7.0.8), specifically leveraging the Scikit-learn library. Historical maintenance data, failure events, and equipment operation parameters were processed to train the model. The selection of the most appropriate failure distribution was carried out through quantitative evaluation, particularly by comparing the Mean Squared Error (MSE) between the actual failure data histogram and the Probability Density Function (PDF) of each statistical distribution tested.

Complementary reliability analysis was conducted through the calculation of MTBF and MTTR, as illustrated in Figure 2. Equipment criticality was ranked based on its financial impact and operational consequences, particularly in terms of MWh Loss. Failure modes were identified by cross-referencing work order data with time-based energy loss logs.

System design also incorporated user needs and was made technically compatible with existing platforms such as ERP and CMMS (IBM Maximo). AI algorithm selection was tailored to match the complexity of the plant's operational data, including load fluctuations, maintenance history, and fault distribution.

The resulting predictive model was integrated into a real-time visualization dashboard, enabling dynamic cost estimation and strategic decision support. This integration also facilitated cross-functional collaboration between engineering, operations, and finance teams, ensuring that budget planning was aligned with actual asset conditions in accordance with ISO 55010 principles.



**Figure 2.** Illustration of MTBF and MTTR Concepts [11].

## 2.4. Development

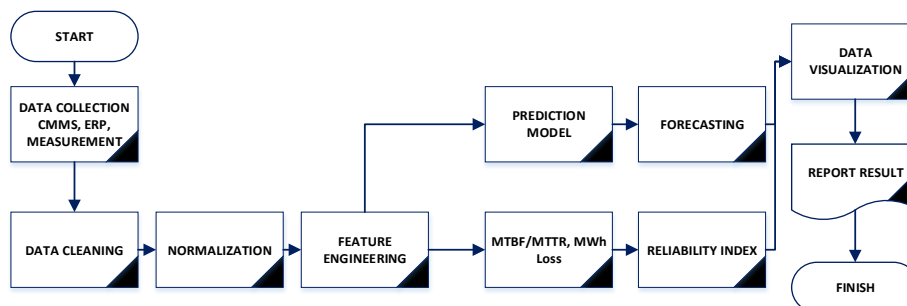
The development phase served as the execution stage for implementing technical solutions derived from the planning and analysis results. It began with the construction of an integrated database that consolidated operational and financial data from Palabuhanratu CFPP, serving as the backbone for predictive processing.

AI-based forecasting algorithms were then developed to estimate future CAPEX and OPEX requirements by analysing historical trends, asset degradation profiles, and unit performance indicators. These algorithms were embedded within a centralized system platform designed for compatibility with existing digital infrastructure, including CMMS (IBM Maximo) and ERP. This ensured seamless data exchange and minimized process duplication across platforms.

To guarantee system accuracy and reliability, a structured quality assurance protocol was implemented. This included code reviews, iterative debugging, and multi-stage testing—comprising

unit testing, integration testing, and user acceptance testing (UAT). UAT involved key stakeholders from both operational and financial departments to validate functionality and usability [11].

Comprehensive system documentation was developed in parallel, covering system architecture, data schema, algorithm logic, and standard operating procedures as shown in Figure 3. This documentation supports long-term maintainability, facilitates user onboarding and training, and ensures system sustainability in future operational cycles.



**Figure 3.** Flow System Predictive and Cost Forecasting.

## 2.5. Implementation

The implementation phase focused on deploying the developed system into the operational environment of Palabuhanratu CFPP. A pilot rollout was first conducted on high-impact subsystems—those contributing significantly to operational costs and reliability issues. This phased approach allowed early assessment of system functionality and enabled feedback from end-users to refine features prior to full-scale deployment.

Following the trial, the system was fully integrated into the plant’s budgeting workflow and existing digital infrastructure, including ERP and CMMS platforms. During integration, a comprehensive risk assessment was conducted, addressing both technical and organizational aspects. Mitigation strategies were implemented, such as fallback procedures, data redundancy protocols, and contingency plans to ensure operational continuity and system resilience [12]

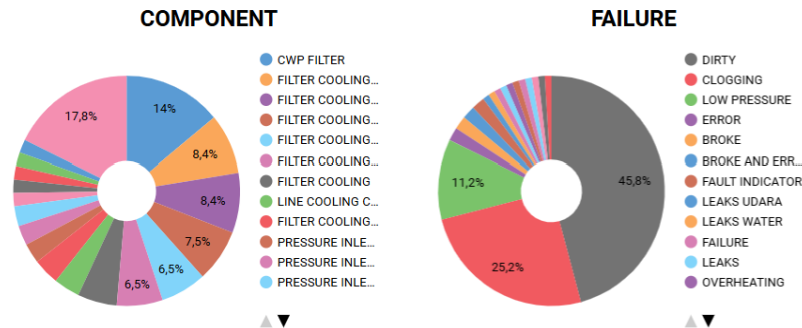
IBM Maximo, the CMMS platform adopted by Palabuhanratu CFPP, plays a central role in asset monitoring and predictive maintenance. It enables centralized management of preventive, corrective, and condition-based maintenance activities, including asset history tracking, workforce scheduling, and inventory control [12].

As illustrated in Figure 4, work order data is synchronized with failure event logs to classify failure modes and affected components. Although the current input system uses open-source formats without automated validation, it remains sufficient for initial reliability analysis. Data updates are conducted regularly to refine the accuracy of reliability metrics, such as failure rate and MTTF.

Processed data is visualized through categorized dashboards—filtered by asset function or tactical relevance and further exported to Python scripts to compute failure rates. These insights allow the planning of targeted maintenance interventions with optimized timing and resource allocation.

Successful implementation was also contingent on organizational readiness and change management. Stakeholder communication, the formation of a change champion team, and a continuous feedback loop were key enablers. A structured training program supported the transition, covering technical modules for IT personnel and operational usage for maintenance teams. These efforts were reinforced with documentation such as user manuals, quick guides, and interactive help systems.

Through this holistic and iterative approach, the system was embedded not only as a digital tool but also as a catalyst for cultural and procedural transformation in maintenance and financial planning—positioning the plant for long-term cost efficiency and performance improvement.



**Figure 4.** Types of Damage and Components on CWP caused by Debris.

## 2.5. Evaluation

The evaluation phase was conducted to assess the system’s effectiveness, accuracy, and integration into the maintenance cost management processes at Palabuhanratu CFPP. Assessment focused on three key dimensions: technical performance, operational usability, and strategic alignment.

From a technical perspective, the predictive model’s accuracy was measured using performance metrics such as Mean Squared Error (MSE) between the actual data histogram and the probability density function (PDF) of each distribution, confirming its reliability in forecasting maintenance costs. Operational evaluation focused on the system’s ability to improve maintenance scheduling, reduce unplanned downtime, and support proactive decision-making. Strategically, the system’s alignment with ISO 55010 principles was assessed, particularly its capacity to integrate financial and technical asset management functions.

User acceptance and interface usability were also evaluated through structured feedback from maintenance, finance, and IT personnel during the User Acceptance Testing (UAT) phase. Key indicators included ease of use, clarity of dashboard outputs, and the perceived value of predictive insights in budgeting decisions.

To support continuous improvement, the system was equipped with real-time monitoring dashboards, periodic data quality audits, and predictive algorithm validation protocols. Feedback mechanisms—such as bug tracking systems, routine evaluation meetings, and user surveys—were implemented to capture and address usability issues, enabling agile refinement of system features.

## 3. Results and Discussion

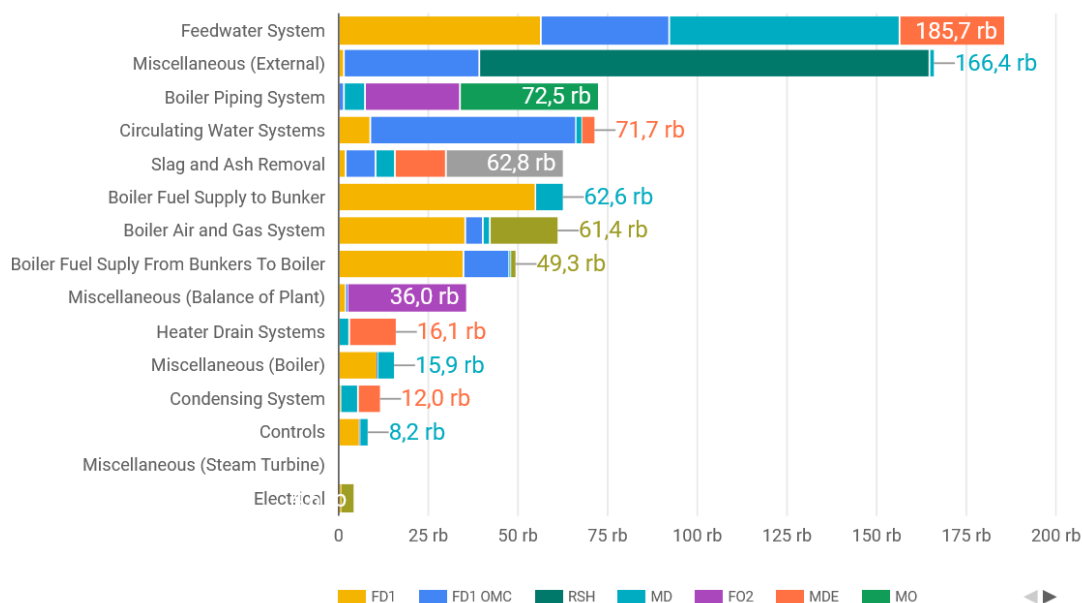
The following section details the technical outcomes of implementing an AI-driven predictive analytics framework for CAPEX and OPEX optimization at Palabuhanratu Coal-Fired Power Plant (CFPP). The discussion integrates multi-source operational datasets, statistical reliability modelling, and financial performance indicators to evaluate system effectiveness. Results are presented in three dimensions: operational performance improvement, measured by reductions in MWh Loss and unplanned downtime; reliability enhancement, quantified through Mean Time Between Failures (MTBF), Probability Density Function (PDF), and Reliability Index analyses; and financial impact, expressed in cost savings and optimized budget allocations. These findings are interpreted in alignment with ISO 55010’s lifecycle asset management framework, emphasizing the correlation

between technical reliability metrics and cost governance efficiency. By employing a data pipeline that integrates Looker Studio dashboards with the ERP/VW system, the plant achieved end-to-end traceability from fault identification to budget planning, enabling precise maintenance prioritization, risk-based CAPEX investment, and evidence-based decision-making.

### 3.1. Integrated Predictive Dashboard Development

Following the analytical and reliability assessment results, the next critical step was to translate these insights into an operational tool that could support day-to-day decision-making. To achieve this, a visual dashboard was developed and deployed using Looker Studio, serving as a strategic enabler for data-centric governance. This platform allows seamless integration of data from multiple sources, such as Google Sheets, enabling real-time visualization of key metrics including energy output loss (MWh Loss), equipment failure history, and detailed component lifecycle predictions. By consolidating technical and financial parameters into an interactive interface, the dashboard empowers both management and technical teams to rapidly detect emerging failure patterns, evaluate their operational impact, and proactively schedule maintenance activities to mitigate unplanned downtimes.

This dashboard is developed to help analyze electricity production losses (MWh Loss) in a more structured and measurable way. It refers to the protocol (Deklarasi Kondisi dan Indeks Kinerja Pembangkit) or Plant Condition Declaration and Performance Index [13], which is standard used in PLN for classifying and reporting operational disturbances.

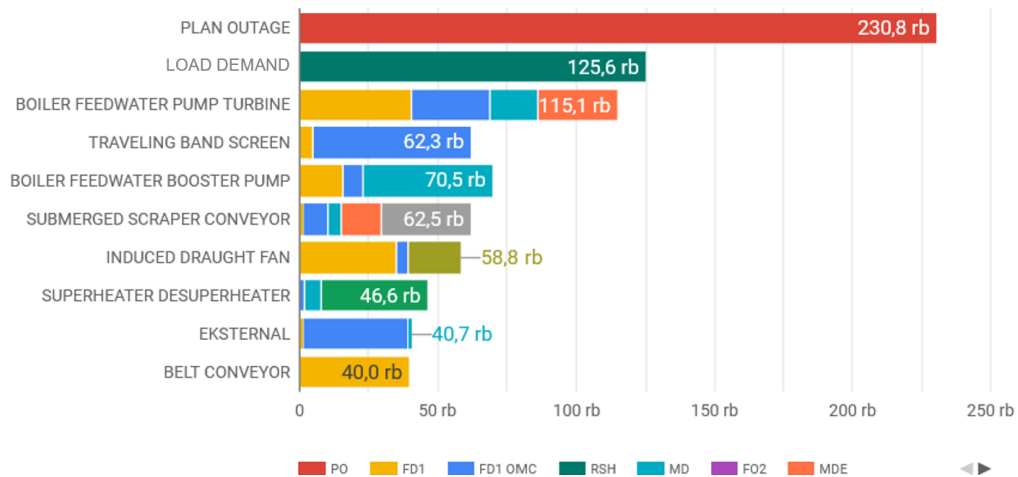


**Figure 5.** Pareto Loss based on Cause Code Level 2.

The dashboard employs a hierarchical “cause code” classification system, standardized under the DKIKP protocol, to structure disturbance data clearly and consistently. As illustrated in Figure 5, this framework organizes operational incidents into multiple layers for effective root-cause analysis. Level 1 identifies the primary system or major component responsible for the disturbance, Level 2 specifies the subsystem or part within that primary system affected by the event, Level 3 provides the most granular details, documenting exact repair actions or failure types, such as overhauls, rewinding, or troubleshooting [13]. By directly linking with daily operational reports, the

dashboard automatically integrates Level 3 data, eliminating manual entry and ensuring uniformity in disturbance categorization.

This structured approach accelerates both operational diagnosis and performance monitoring across power plant units, aligning fully with PLN Group’s official procedures. The system further enhances operational visibility by offering equipment-specific visualizations, enabling teams to prioritize maintenance activities based on reliability impact and production loss risk.



**Figure 6.** Pareto Loss by Equipment and MWh Loss.

In parallel, the platform features an equipment monitoring dashboard, as shown in Figure 6, which aggregates failure data by both main and supporting equipment. Key parameters—such as failure frequency, downtime duration, and historical trends—are automatically compiled, allowing engineers to identify high-impact assets and allocate resources effectively.

Moreover, full integration with the ERPVW system consolidates historical CAPEX and OPEX data, actual maintenance expenditures, and technical assessment records into a unified information environment. This ERP–CMMS synchronization enables streamlined maintenance prioritization, budget forecasting, and investment feasibility assessment. Together, these capabilities establish a comprehensive, data-driven asset management framework that strengthens OPEX and CAPEX governance while minimizing unplanned downtime and maximizing operational reliability.

Through this integrated dashboard system, Palabuhanratu CFPP gains not only detailed and dynamic operational visualization but also the capability to implement value-based asset management strategies in accordance with ISO 55010 standards as seen in Table 1. ISO 55010 emphasizes the need for aligning technical and financial decision-making processes over the full asset lifecycle to achieve cost-efficiency, operational transparency, and sustainable infrastructure performance. Ultimately, the combined use of Looker Studio and ERPVW not only reinforces the plant’s cost and maintenance management systems but also strengthens its strategic position to respond effectively to operational demands and the evolving challenges of the energy sector.

**Table 1.** Budget Allocation Displayed in ERPVW

No.PR	Judul PR	User	Is EPI?	Status	Create	No.PO	Amount PR (Rp)	Unit	Detail
1604230736	Pengadaan Cartridge Safety Filter RO (APO 2023)	AGUS TOMI	N	Approved	27-SEP-23	1604000718	1.529.304.498	JPR	<a href="#">detail</a>
1604230746	Jasa Pemeliharaan Rutin Jaring Apung, Jaring Portable, Bar Screen Dan Travelling Band Screen (TBS) Intake CWP (APO 2023)	AGUS TOMI	N	Approved	29-SEP-23	1604000745	631.681.628	JPR	<a href="#">detail</a>
1604231112	Pengadaan Filter Compressor SAC & IAC	AGUS TOMI	N	Approved	28-NOV-23	1604000891	134.021.715	JPR	<a href="#">detail</a>
1604231140	Pengadaan Mechanical Seal Pompa dan Membrane Valve BOP (APO 2023)	AGUS TOMI	N	Approved	01-DEC-23	1604000875	115.750.800	JPR	<a href="#">detail</a>
1604231141	Jasa Rekondisi dan Fabrikasi Pompa DSP RIRO SI unit 1 (APO 2023)	AGUS TOMI	N	Approved	01-DEC-23	1604000787	840.936.000	JPR	<a href="#">detail</a>
1604240028	Pengadaan Pneumatic Valve Pada Ultrafiltration SI Unit 1	AGUS TOMI	N	Approved	11-JAN-24	1604000958	282.224.160	JPR	<a href="#">detail</a>
1604240038	Jasa rekondisi dan fabrikasi part CWP Persiapan Riro SI Unit 1	AGUS TOMI	N	Approved	17-JAN-24	1604000980	372.660.300	JPR	<a href="#">detail</a>
1604240072	Jasa Penggantian Pipa Jalur Service Water	AGUS TOMI	N	Approved	26-JAN-24	1604001095	329.308.584	JPR	<a href="#">detail</a>
1604240093	Pengadaan Part Travelling Band Screen (TBS) SI Unit 1	AGUS TOMI	N	Approved	01-FEB-24	1604000965	101.942.400	JPR	<a href="#">detail</a>
1604240124	Pengadaan Manual Valve Spray TBS SI Unit 1	AGUS TOMI	N	Approved	15-FEB-24	1604000970	70.152.000	JPR	<a href="#">detail</a>

Showing 1 to 10 of 39 entries

Previous 1 2 3 4 Next

The dashboard includes a per-equipment disturbance analysis module designed to enhance precision in identifying and addressing high-impact assets. It consolidates historical and real-time data on disturbance frequency, downtime duration, and each asset’s contribution to total MWh Loss within a defined period. This targeted view enables rapid identification of top contributors and tracking of performance degradation trends over time.

The feature supports risk-based maintenance planning, evaluation of spare parts replacement effectiveness, and prioritization of CAPEX for equipment approaching the end of its service life. Integration with field inspection data and technical assessments from the ERP/VW system ensures a unified approach, linking operational performance with financial decision-making. Analysis highlighted a significant increase in disturbance frequency in the Circulating Water Pump (CWP) area. Predictive modelling determined probable failure timelines, enabling preventive measures to avoid unplanned outages and sustain continuous power generation.

### 3.2. Reliability and Statistical Analysis for Critical Equipment

Building upon insights from the per-equipment disturbance analysis, the next phase focuses on converting these operational findings into measurable reliability metrics through statistical modelling. This approach enables accurate estimation of failure probabilities, remaining useful life (RUL), and optimal maintenance schedules for critical assets. Four statistical distribution models—Weibull, Exponential, Lognormal, and Normal—were evaluated using historical failure data, with model selection based on the lowest Mean Squared Error (MSE) and goodness-of-fit tests.

For the “Circulating Water Pump 3B” dataset, the Weibull distribution emerged as the most suitable model as seen in Table 2. The results show a P-value of 0.823, indicating no significant deviation from the null hypothesis, and a Kolmogorov–Smirnov (KS) statistic of 0.054, reflecting minimal difference between empirical and theoretical distributions. Its MSE of 0.0021 is lower than those of the Exponential (0.0045), Lognormal (0.0052), and Normal (0.0080) models, confirming Weibull’s superior reliability prediction capability for this asset.

**Table 2.** Statistical Analysis Results for Circulating Water 3B.

Descriptions	Metric	Value
CIRCULATING WATER 3B	Best Distribution	Weibull
	P-Value	0.823
	KS Statistic	0.054
	MSE	0.0021
	Param1	1.45
	Param2	5000
	MSE_Weibull	0.0021
	MSE_Exponential	0.0045
	MSE_Lognormal	0.0052
	MSE_Normal	0.008

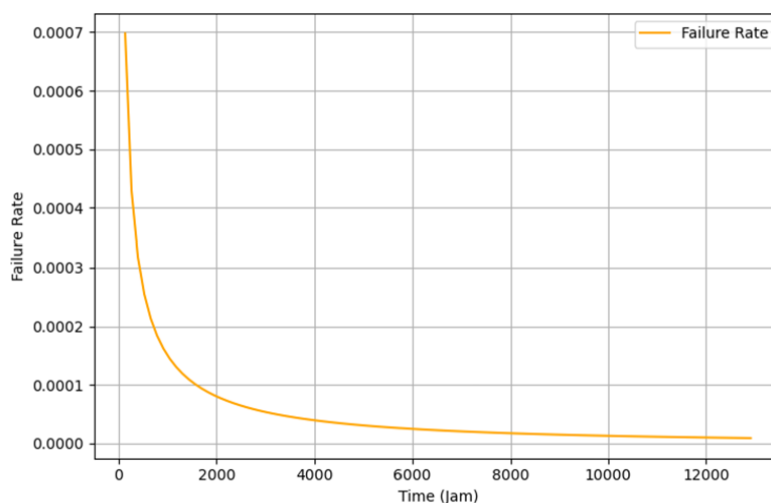


**Figure. 7** Debris Accumulation at The Intake.

Based on the preceding calculations, a comprehensive feasibility assessment was conducted to determine the most effective mitigation measures, as illustrated in Figure 7. The analysis revealed that the accumulation of debris in the intake area was causing clogging in the Circulating Water Pump (CWP) filters. This blockage not only impaired water flow efficiency but also contributed to an estimated 30% increase in operational expenditures (OPEX) due to accelerated equipment wear and damage. Furthermore, the resulting reduction in cooling efficiency led to measurable MWh losses, translating into significant financial impacts. To address this, a targeted investment decision was made to install floating debris nets. These nets serve as a preventive barrier, reducing the ingress of solid waste into the system, thereby lowering the risk of damage to critical components and ensuring sustained operational performance.

Following the prioritization process—which integrates MWh loss data, failure frequency records, technical assessment outcomes, and historical maintenance costs—the next stage involves conducting a detailed Reliability Index analysis. This analysis identifies the optimal point in each asset’s lifecycle where maintenance costs begin to escalate rapidly while reliability declines. By mapping the correlation between reliability scores and maintenance expenditure trends, decision-makers can pinpoint the inflection point where asset replacement or rehabilitation becomes most cost-effective. This approach aligns with ISO 55010 principles, ensuring value-based, lifecycle-oriented asset management.

Accurate Mean Time Between Failures (MTBF) data further enhances this process by enabling predictive failure modelling. This allows for the establishment of an early warning system, facilitating preventive maintenance scheduling and minimizing unplanned downtime. Consequently, budget allocation for both CAPEX (equipment replacement) and OPEX (routine servicing) can be planned with greater precision, improving cost efficiency and reducing operational risks. For Palabuhanratu CFPP, this strategy is crucial to meeting production targets while maintaining system reliability in the Java–Bali grid, ultimately preventing revenue losses from unexpected outages.



**Figure. 8** Failure Rate vs Time.

By calculating MTBF parameters using Python-based statistical modelling, key information such as the Probability Density Function (PDF), Cumulative Distribution Function (CDF), and Reliability Index can be derived as shown in Figure 8. These parameters provide a probabilistic insight into the expected failure time of equipment, enabling more precise, condition-based maintenance strategies. This information can then be used to build a responsive and adaptive budget allocation system, particularly in determining appropriate OPEX values based on actual maintenance needs. Furthermore, when reliability-based cost trends show a significant increase, the system can automatically recommend asset replacement. Thus, the transition from OPEX to CAPEX can be better planned and data-supported, helping management optimize asset lifecycles and avoid inefficient repetitive maintenance. This approach forms a fundamental pillar of modern data-driven asset management, consistent with ISO 55000 standards and AI-driven predictive maintenance practices.

### 3.3. Financial and Operational Impact

Complementing the technical results, the financial impact of the predictive AI-driven cost management system was evaluated to quantify its contribution to plant performance. A before–after analysis of operations and maintenance records shows clear gains in both cost efficiency and production reliability. Energy production losses fell from 72.7 GWh to 43.1 GWh ( $\Delta = 29.6$  GWh); valued at the prevailing electricity tariff of USD 74000/GWh (for Pelabuhan Ratu 3x350MW CFPP), this corresponds to  $\approx$  USD 2.19 million in avoided losses. In parallel, maintenance expenditures declined from USD 144,000 to USD 41,867 over the same evaluation period, primarily because the system detected early signs of asset degradation, enabling timely interventions and prioritization of critical equipment. Taken together, these results indicate that integrating predictive analytics into

CAPEX and OPEX planning not only reinforces technical reliability but also yields measurable financial benefits, aligning with ISO 55010's emphasis on linking asset performance to cost optimization.

#### **4. Conclusion**

This study successfully achieved its objective of developing and implementing a predictive artificial intelligence (AI)-driven cost management system aligned with ISO 55010 principles, aimed at optimizing Capital Expenditure (CAPEX) and Operational Expenditure (OPEX) while improving maintenance cost accuracy at the Palabuhanratu coal-fired power plant (CFPP).

By integrating AI algorithms, historical operational data, technical assessments, and reliability analysis, the proposed system has demonstrated a significant improvement in maintenance budget planning accuracy, CAPEX/OPEX allocation, and overall operational reliability and efficiency. The results show a substantial reduction in energy production losses, with MWh loss decreasing from 72.7 GWh to 43.1 GWh—equivalent to approximately USD 2.19 million per period in savings. In parallel, maintenance costs were reduced from USD 34,000 to USD 41,867 within the same period.

The deployment of an interactive dashboard via Looker Studio, integrated with ERP VW, DKIKP, and CMMS (Maximo), has further enhanced data-driven decision-making by enabling real-time monitoring, cross-functional analysis, and alignment between financial planning and actual asset conditions.

The outcomes, including reduced downtime, improved cost efficiency, and higher unit readiness, demonstrate that predictive strategies aligned with ISO 55010 can serve as an effective solution for CAPEX and OPEX optimization. Beyond Palabuhanratu CFPP, this framework holds strong potential for replication across other PLN Group power plants. Ultimately, the proposed approach establishes a solid foundation for a sustainable, intelligent, and digitally transformed national asset management system.

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