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Optimal Maintenance Strategy Selection Under Budget and Performance Constraints in Coal-Fired Power Plant

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Abstract: *Maintenance planning in coal fired power plants involves complex tradeoffs between budget limitations and operational performance targets. However, existing approaches generally treat cost and performance considerations separately, resulting in suboptimal decision making. This study addresses this gap by proposing a multi constraint decision making framework that simultaneously integrates budget constraints and key performance indicators, including equivalent availability factor (EAF), equivalent forced outage rate (EFOR), and net plant heat rate (NPHR). The proposed model employs integer linear programming with binary decision variables to determine the optimal combination of maintenance programs under predefined constraints, while incorporating mandatory maintenance requirements. The results demonstrate that the model can improve the benefit cost ratio from 73,6% to 75.7% while reducing the maintenance budget by up to 11.25% and identify a minimum feasible budget of Rp 417 billion to satisfy all performance targets. Furthermore, the analysis reveals a nonlinear relationship between budget allocation and system performance, with reliability indicators showing higher sensitivity to budget reductions. These findings provide a structured and transparent decision support tool for maintenance planning in coal fired power plants under constrained resources.*

Keywords: *budget constraint, coal fired power plant, integer linear programming, maintenance optimization, performance constraint*

1. Introduction

Power generation systems, particularly coal fired power plant, operate with large and complex assets bases that require continuous maintenance to ensure reliability, availability, and efficiency. In the context, maintenance planning plays a critical role in sustaining operational performance while managing significant operational expenditures. The increasing demand for cost efficiency, especially in cost centre organizations, has intensified the need for structured and data driven approaches in developing annual maintenance work plans and budgets [1].

In practice, maintenance planning in power plants is typically based on routine classifications such as preventive, predictive, corrective, and overhaul activities. However, the selection and prioritization of these programs are often conducted without a rigorous quantitative evaluation of their contributions to key operational performance indicators, such as equivalent availability factor (EAF), equivalent forced outage rate (EFOR), and net plant heat rate (NPHR). As a result, decision making tends to rely on experience and heuristic judgement, which may lead to suboptimal allocation of limited maintenance budgets.

Extensive research has been conducted to improve maintenance decision making through various approaches. Reliability based and economic optimization models have been developed to support maintenance planning and budget allocation [3,8], while system dynamics and cost benefit frameworks have been applied to maximize long term economic value [16]. In parallel, multi criteria decision making methods such as analytical hierarchy process (AHP) and goal programming have been widely used to incorporate multiple performance aspects, including availability and risk, into maintenance strategy selection [15,18]. Furthermore, optimization-based techniques, including mixed integer linear programming, constraint programming, stochastic decision processes, and risk-based cost and benefit optimization have been applied to maintenance scheduling and resources allocation problems [7-9].

Despite these advancements, existing studies predominantly address cost, reliability, and performance metrics in isolation. Optimization based models largely focus on reliability or scheduling aspect without explicitly incorporating operational performance indicators such as EAF, EFOR, and NPHR into a unified decision framework. Meanwhile, multi criteria approach often rely on qualitative or semi quantitative assessments, limiting their scalability and applicability for large scale maintenance program selection. In addition, current studies rarely establish a direct quantitative linkage between maintenance actions and their economic impact, particularly in terms of monetized performance improvements.

Consequently, there is a lack of a structured optimization framework that simultaneously integrates budget constraint, performance targets, and economic valuation into a single decision-making model applicable to real world power plant maintenance planning. This gap is particularly critical in coal fired power plants, where maintenance decision directly influence both operational performance and financial outcomes.

To address this gap, this study proposes a multi constraint optimization framework for maintenance program selection that explicitly integrates budget limitations with key performance indicators namely EAF, EFOR, and NPHR. The proposed model is formulated using integer linear programming with binary decision variables enabling the systematic selection of maintenance programs while considering mandatory activities and minimum performance targets. By converting performance improvements into economic values, the model provides a quantitative basis for evaluating trade-offs between cost and performance.

The contribution of this study lies in the development of an integrated decision support framework that bridges engineering performance metrics and financial planning in maintenance management. The proposed approach not only enables the identification of optimal maintenance program combinations under constrained budgets but also provides transparent and quantitative insights to support planning and evaluation processes in power plant operations.

2. Method

2.1. Data Collection and Parameter Definition

Maintenance data are obtained from plant operational records, including maintenance alternatives, associated cost, and historical performance data. Key performance indicators considered are EAF, EFOR, and NPHR. Each maintenance activity is characterized by cost, performance impact, and classification as mandatory or optional. Performance improvements are monetized into Indonesian Rupiah to enable economic evaluation.

2.2. Model Formulation

The problem is formulated as an integer linear programming (ILP) model with binary decision variables.

- Decision between variables
  Binary variables Xi representing the selection of maintenance program i, where
  $$X_i = 0 \ or \ \ X_i = 1 \tag{1}$$
- Budget Constraints
  The total cost of selected maintenance programs must not exceed the available maintenance budget:
  $$\sum_{i=1}^{i} X_i . C_i \leq C_{max} \tag{2}$$
  where Ci represents the cost of maintenance program I (in Indonesian Rupiah), and Cmax denotes the total available maintenance budget (in Indonesian Rupiah).
- Performance Constraint

The selected maintenance programs must satisfy minimum performance requirements to ensure that the operational targets of the power plant are maintained. These requirements are defined in terms of performance indicators which represents its monetized benefit and expressed in Indonesian Rupiah

1). MEAF

To guarantee sufficient system availability, the aggregated contribution of selected maintenance programs must achieve at least the predefined minimum EAF target, as formulated in:

$$\sum_{i=1}^{i} X_i.PEAF \geq MEAF \quad (3)$$

where PEAF represents the improvement in equivalent availability factor contributed by maintenance programs, reflecting the economic value of increased availability through additional power generation and reduced production losses. MEAF denotes the minimum required equivalent availability factor that must be achieved.

2). MEFOR

To ensure system reliability, the aggregated effect of selected maintenance programs must reduce the equivalent forced outage rate to within the allowable limit, as formulated in:

$$\sum_{i=1}^{i} X_i.PEFOR \geq MEFOR \quad (4)$$

where PEFOR represents the reduction in equivalent forced outage rate contributed by maintenance programs, representing the economic benefit of avoided forced outages, including reduced unplanned downtime and prevention of generation losses. MEFOR denotes the maximum allowable equivalent forced outage rate that must not be exceeded.

3). MNPHR

To ensure adequate thermal efficiency, the aggregated contribution of selected maintenance programs must reduce the net plant heat rate to within the acceptable limit, as formulated in:

$$\sum_{i=1}^{i} X_i.PNPHR \geq MNPHR \quad (5)$$

where PNPHR, represents the reduction in net plant heat rate contributed by maintenance program, reflecting the economic benefits derived from improved thermal efficiency by reducing fuel consumptions. MNPHR denotes the maximum allowable net plant heat rate that must be exceed.

- Mandatory maintenance constraint

  Mandatory maintenance actions are enforced within the model to ensure compliance with operational requirements as

$$X_i = 1 \quad (7)$$

2.3. Optimization procedure

The Integer Linear Programming (ILP) model is solved using an optimization solver to determine the optimal combination of maintenance programs. The formulation enables a direct linkage between engineering performance improvements and financial outcomes, allowing maintenance decisions to be evaluated on a quantitative economic basis. The objective is to maximize the total benefit derived from selected maintenance programs:

$$Max\ Z = \sum_{i=1}^{i} X_i(PNPHR_i + PEAF_i + PEFOR_i) \quad (8)$$

Optimization model aims to represents maximize the total benefit obtained from the selected maintenance programs. The coefficient associated with each program represents its monetized benefit and expressed in Indonesian Rupiah, which is derived from improvements in key performance indicators, namely equivalent availability factor (PEAFi), equivalent forced outage rate (PEFORi), and net plant heat rate (NPHRi). By summing the benefits of all selected programs, the objective function identifies the combination of maintenance activities that yields the maximum total benefit while satisfying all constraints. This ensures that the selected maintenance strategy not only meets operational requirements but also delivers the highest possible economic value

2.4. Sensitivity and scenario analysis

The sensitivity analysis is conducted using deviation-based measures, where the percentage change in input (budget) and output (KPI) is calculated. The sensitivity is then evaluated as the ratio between output deviation and input deviation. The deviations are calculated using the following equations:

$$Dev_{input,i} = \frac{budget_i^{up} - budget_i^{down}}{budget_i^{base}} x\ 100\% \quad (9)$$

$$Dev_{output,i} = \frac{KPI_i^{up} - KPI_i^{down}}{KPI_i^{base}} x\ 100\% \quad (10)$$

2.5. Model Validation

To quantitatively assess the performance of the proposed optimization model, a statistical validation is conducted by optimality gap analysis to evaluates how close the obtained solution is to the best possible (optimal) solution:

$$Gap = \frac{z_{max} - z_{obt}}{z_{max}} x\ 100\% \quad (11)$$

where Zmax is optimal objective value and Zobt is solution value. For exact LINGO program, this gap is typically 0%, indicating global optimality.

3. Results and Discussion

3.1. Optimization Results

The model was applied to a 1,391 MW coal fired power plant. As shown in table 1, the baseline scenario, where all maintenance programs are executed, results in a budget of Rp. 507 billion and a benefit of Rp. 373.0 billion/year, yielding a Benefit to Cost Ratio (BCR) of 73.6%. However, this approach includes low impact programs, leading to reduced efficiency.

TABLE I: Comparison of optimization results

Parameter	Baseline	Scenario 1 (Max KPI)	Scenario 2 (Min Budger)
Budget (Rp Billion)	507	450	417
Benefit (Rp Billion/year)	373.0	340.5	312.7
Benefit cost ratio (%)	73.6	75.7	75.0
Budget efficiency (%)	-	11.25	21.58
Benefit reduction (%)	-	8,71	19.28

In scenario 1, the budget is reduced to Rp. 450 billion while maintaining all performance constraints. The model selectively excludes noncritical programs, resulting in only an 8.71% reduction in benefit but an 11.25% reduction in cost. Consequently, the BCR increases to 75.7%, representing the most efficient allocation.

Scenario 2 identifies the minimum feasible budget of Rp. 417 billion. Although all performance targets are still satisfied, but the benefit decreases by 19.28%, indicating reduced system robustness and limited operational flexibility.

3.2. Influence of KPI constraints on optimization

The inclusion of EAF, EFOR, and NPHR significantly shapes the feasible solution space. Among these indicators, EFOR emerges as the most influential parameter. Since EFOR is directly associated with forced outages, even small increases can result in substantial production losses. thereby significantly reducing economic benefit. As a result, the optimization model prioritizes maintenance programs that effectively reduce EFOR. This behaviour highlights that reliability driven maintenance actions dominate the selection process, even when cost reduction is a primary objective. This observation is further supported by the sensitivity trend shown in Fig.1, where EFOR exhibits the steepest response to budget variation.

EAF, while also related to availability, exhibits a more gradual response to maintenance investment. Improvements in EAF are typically cumulative and do not exhibit abrupt changes unless major failures occur. Therefore, its influence on the optimization outcome is moderate compared to EFOR, as also reflected in Fig.1, where slope is less pronounced.

In contrast, NPHR demonstrates the lowest sensitivity to budget variation. As an indicator of thermal efficiency, NPHR improves incrementally through maintenance actions such as heat transfer surface cleaning or performance tuning. However, its impact on overall benefit is relatively gradual and does not involve sudden losses, making it less dominant in the optimization process. This behaviour is consistent with Fig.1, where NPHR exhibits the flattest trend among the KPIs.

3.3. Budget performance relationship and nonlinearity.

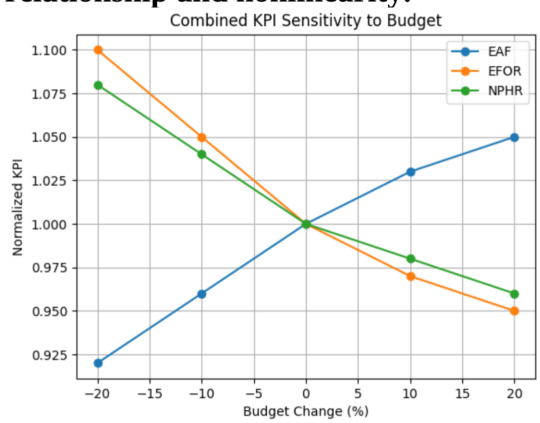

Fig. 1: Combined KPI sensitivity to budget.

As shown in Fig.1. a nonlinear relationship exists between maintenance budget and system performance. The figure presents the normalized response of EAF, EFOR, and NPHR under budget variations from -20% to +20%.

Increasing the budget improves all KPI's, with EAF rising gradually, EFOR decreasing significantly, and NPHR improving moderately. The steep decline in EFOR indicates that reliability is the most sensitive to maintenance investment. In contrast, reducing the budget leads to a disproportionate increase in EFOR, while changes in EAF and NPHR remain more gradual, highlighting system vulnerability to insufficient maintenance.

The asymmetry in response confirms the presence of diminishing returns, where performance improvements become marginal at higher budget levels but deteriorate rapidly under budget reduction. The convergence at the baseline condition further indicates a reference operating point from which deviations produce nonlinear effects.

A critical budget threshold is identified at approximately Rp 417 billion, below which system performance, particularly reliability, degrades significantly. Operating near this level increases operational risk, as further budget reduction would violate performance constraints.

3.4. Trade-off between cost and performance

The results highlight a trade-off between cost, reliability, and efficiency

- Cost vs reliability:

  Reducing the maintenance budget leads to a noticeable increase in EFOR, indicating that reliability is highly sensitive to cost reduction. A relatively large value of sensitivity means that even a small decrease in budget can cause a significant increase in forced outages. This occurs because reliability related maintenance activities play a key role in preventing failures. When these activities are reduced, the likelihood of unplanned outages increases.

In addition, higher EFOR directly leads to loss of generation and revenue. Therefore, although reducing the budget may lower maintenance costs, it can result in larger economic losses due to decreased reliability. This explains why the optimization model prioritizes maintenance programs that reduce EFOR

- Cost vs efficiency

  Reducing the maintenance budget results in a gradual increase in NPHR, indicating a decline in thermal efficiency. Compared to EFOR, the value of sensitivity is relatively smaller, showing that efficiency is less sensitive to budget changes. This is because efficiency improvements are typically incremental, achieved through activities such as improving heat transfer or performance tuning. As a result, budget reduction leads to a gradual deterioration in efficiency rather than a sudden impact.

  From an economic perspective, higher NPHR increases fuel consumption and operating costs. However, the impact is more progressive and does not cause immediate losses, making efficiency less dominant in the optimization process

- Cost vs availability

  Reducing the maintenance budget also leads to a decrease in EAF, indicating lower system availability. The sensitivity of EAF is moderate compared to EFOR and NPHR. Availability improves through cumulative maintenance efforts and tends to change more gradually. While reduced budget lowers maintenance coverage and slightly decreases availability, the effect is not as immediate or severe as the increase in forced outages.

  Economically, lower EAF reduces overall generation capacity (derating), but its impact is typically less abrupt than forced outages. Therefore, availability plays a supporting role in the optimization process, positioned between reliability and efficiency in terms of sensitivity

The optimization consistently prioritizes reliability over efficiency, indicating that preventing outages provides greater economic value than incremental efficiency improvements.

4. Conclusion

This study developed an ILP based framework for maintenance planning that integrates budget constraints with performance indicator. The model improves the benefit cost ratio from 73.6% to 75.7% while reducing the maintenance budget by 11.25% (from Rp. 507 billion to Rp. 450 billion), with only an 8.71% reduction in benefit. In addition, a minimum feasible budget of Rp. 417 billion is identified, at which all performance constraints are still satisfied.

The findings reveal a nonlinear relationship between budget allocation and system performance, where reliability (EFOR) is the most sensitive parameter, while efficiency (NPHR) changes more gradually. This indicates that reliability driven maintenance dominates decision making, as preventing forced outages yields higher economic value than incremental efficiency improvements. A key finding is the existence of a critical budget threshold (Rp. 417 billion), below which system performance deteriorates rapidly, along with diminishing returns at higher budget levels.

From a practical perspective, scenario 1 provides the best balance between cost and performance, while scenario 2 represents a minimum cost strategy with higher operational risk. The main contribution of this study is development of a multi constraint optimization framework that that quantitatively captures trade-offs between cost, reliability, and efficiency, and provides a transparent decision support tool for maintenance planning

5. Acknowledgements

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