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Machine learning enabled preventive maintenance strategy for improving boiler reliability of a thermal power station

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Abstract

Coal-fired power stations remain critical to electricity security in Zimbabwe, yet their contribution is weakened when boiler failures increase forced outages, maintenance costs and generation instability. This paper improves and consolidates a case study of Local Thermal Power Station Stage 2 in Zimbabwe, by developing a model to optimise a preventive maintenance strategy for boiler reliability. The study analysed a 13-year monthly operating dataset from 2010 to 2023, stakeholder evidence on existing maintenance practices, reliability trends, plant availability, generation output, boiler efficiency, failures, maintenance cost and mean time between maintenance. Several machine-learning classifiers were evaluated, and the Random Forest classifier was selected for the preventive maintenance decision model due to its superior predictive performance and suitability for non-linear operational data. The results show that the existing maintenance strategy is highly reactive, with corrective maintenance accounting for about 72% of the strategy mix. The long-term reliability profile was depressed relative to world-class thermal power plant expectations and declined gradually across the review period. The developed model identified an optimal reliability point of about 66%, associated with improved availability, an average generation of 154.26 MW, electricity sent out of 43.7 GWh, a mean time between maintenance of 300 hours, reduced predicted maintenance costs, and fewer boiler failures. Validation against the first 16 weeks of 2024 indicated a strong positive relationship between predicted and actual outcomes, while also showing a performance gap between current practice and model-optimised values. The paper argues that a data-driven preventive maintenance model can support more disciplined boiler maintenance planning, reduce unplanned outages, and strengthen electricity supply reliability in coal-fired power stations.

Keywords: Boiler Preventive Maintenance; Coal-Fired Power Station; Machine Learning; Random Forest; Reliability Optimisation

1. Introduction

Reliable power generation is central to national development, industrial productivity, and social welfare. In Zimbabwe, the main Thermal Power Station remains the dominant coal-fired generation asset, and the performance of its boilers directly affects the security of the electricity supply. Although new capacity from Units 7 and 8 has provided relief to the national grid, the older generating units continue to experience forced outages and performance instability. This study focuses on Stage 2, which consists of two 150 MW units whose boiler reliability has become a practical maintenance and operational concern.

Boilers are complex, high-temperature, and high-pressure assets. Their performance depends not only on design and age, but also on the discipline with which inspection, cleaning, calibration, lubrication, repair planning, spares provision and condition monitoring are carried out. When maintenance is dominated by corrective work after failure, the plant

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may remain trapped in a cycle of emergency work, high costs, reduced availability, and declining confidence in generation forecasts. Preventive maintenance is therefore not merely a technical routine; it is a strategic reliability instrument.

The central problem addressed in this paper is that the preventive maintenance strategy at the main Thermal Power Station Stage 2 has not been sufficiently optimised to account for actual boiler operating conditions, maintenance resources, and reliability targets. Existing maintenance practices have tended to respond to breakdowns rather than predict and prevent them. These issues reduce plant availability and increase the risk of load shedding. The paper therefore develops and tests a machine-learning-enabled preventive maintenance planning model that can support decision-making on boiler reliability.

The contribution of this study is threefold. First, it provides an empirical assessment of the current maintenance strategy mix and locates the plant on the maintenance cost curve. Second, it analyses Stage 2 boiler reliability against expected world-class thermal power plant performance. Third, it develops and validates a random forest-based model that links maintenance planning decisions to reliability, maintenance cost, boiler failures, plant availability, average generation, boiler efficiency, and mean time between maintenance.

2. Literature Review

2.1. Preventive maintenance and boiler reliability

Maintenance is the organised care of assets so that they continue to perform their intended functions safely, efficiently and economically. In a thermal power station, this includes inspection, cleaning, calibration, monitoring, repair, component replacement, and reliability analysis. Preventive maintenance differs from breakdown maintenance because it seeks to act before functional failure occurs. Its value lies in reducing unplanned downtime, improving asset life and providing a more stable basis for generation planning.

For utility boilers, preventive maintenance is especially important because boiler pressure parts, burners, fans, mills, valves, instrumentation, and control systems operate under severe thermal and mechanical conditions. Patil et al. [1] revealed that reliability-centred maintenance can be applied to develop an optimised maintenance programme for steam boiler systems by linking failure modes to criticality and maintenance tasks. Application of reliability-centered maintenance is relevant to the Local Thermal Power Stations because boiler failures do not affect only one component; they cascade into availability, sent-out energy, maintenance expenditure, and system reliability.

Condition-based and reliability-based maintenance models have become important extensions of conventional time-based preventive maintenance. Condition-based maintenance uses inspections, sensors and diagnostics to decide when intervention is justified, while reliability-based models use probability of failure, remaining useful life and criticality to prioritise work. Studies on boiler-room sustainability, maintenance optimisation and maintenance economics show that preventive decisions are strongest when they link technical condition, cost and operational consequence rather than treating maintenance as a fixed calendar activity [2-5]. A hybrid approach is often more appropriate for power stations because not every boiler component has the same failure behaviour, and not every maintenance task has the same consequence if deferred.

2.2. Machine learning in maintenance planning

Machine learning extends maintenance planning by learning patterns from historical operating and failure data. Algorithms such as Random Forest, Decision Trees, Logistic Regression, Support Vector Machines, K-Nearest Neighbours, AdaBoost, and XGBoost can classify or predict operating states when sufficient data are available. General machine-learning reviews and Industry 4.0 studies confirm the broad relevance of these algorithms for industrial decision support, while predictive-maintenance comparisons show the value of ensemble methods such as Random Forest in equipment-failure contexts [6-10]. In maintenance contexts, the main purpose is not to replace engineering judgement but to convert scattered historical evidence into repeatable decision support.

Reviews of industrial maintenance decision-making show that data-driven methods can strengthen maintenance planning when they are combined with domain knowledge and clear performance measures [11, 12]. Random Forest is attractive for this study because it handles non-linear relationships, mixes numerical and categorical predictors, reduces overfitting through ensemble learning, and provides interpretable measures of feature importance. These characteristics are well-suited to boiler maintenance data, where reliability is influenced by several interacting variables rather than a single isolated factor.

The literature also cautions against adopting machine learning as a stand-alone solution. Maintenance models must be validated against actual operating outcomes, updated as plant conditions change, and embedded in the work management system. The present study responds to this requirement by validating model outcomes against the first 16 weeks of 2024 and by comparing the practical gap between current performance and model-optimised values.

2.3. Conceptual framework for the study

The conceptual position adopted in this paper is that the interactions among maintenance strategy, operating conditions, and decision timing shapes boiler reliability. A maintenance strategy that is mainly corrective waits for failure evidence to become visible through forced outage, component damage or performance loss. A preventive strategy uses planned intervals and inspections to reduce this exposure, while a predictive or condition-based strategy uses evidence from the plant to determine where intervention will have the greatest reliability effect. The proposed model therefore sits between preventive and predictive maintenance: it uses historical data to improve the timing and priority of preventive actions.

The framework links inputs, model logic, and outputs. The inputs include monthly reliability, number of boiler failures, maintenance cost, average generation, plant availability, boiler efficiency, and mean time between maintenance. The model logic uses supervised machine learning to learn the relationship between these variables and the reliability outcome. The outputs are decision-support indicators that allow maintenance managers to compare current practice with an optimum region. This structure is important because it avoids treating reliability as an isolated percentage. Instead, reliability is interpreted alongside the costs and operational consequences of maintenance decisions.

In this study, the reliability optimum is not presented as a permanent universal value. It is an operating region produced from the historical behaviour of Stage 2 and should be refined as new data are captured. This is consistent with engineering practice: maintenance optimisation must remain dynamic because coal quality, unit loading, spares availability, outage schedules and equipment age all change over time. The model is therefore best understood as a living decision aid that can be updated as the power station improves its data quality and implements more disciplined preventive maintenance routines.

3. Research Methodology

The study adopted a case-study design focused on the main Thermal Power Station Stage 2 in Zimbabwe: the methodological approach combined maintenance strategy assessment, statistical reliability analysis, and machine-learning model development. The study used a 13-year monthly dataset covering the period 2010 to 2023, together with stakeholder inputs from questionnaires, interviews, visual inspection and maintenance records. A mixed-evidence base was selected as boiler reliability is both a data and an organisational maintenance problem.

The first objective assessed the effectiveness of the maintenance strategy being implemented at the power station. The analysis considered the maintenance strategy mix, focusing on corrective, preventive, predictive, and proactive maintenance. The maintenance strategy was also interpreted against the total maintenance cost curve, because both under-maintenance and over-maintenance can increase cost. The purpose was to determine whether the current strategy was positioned near the economic reliability optimum or whether it remained biased toward reactive work.

The second objective analysed Stage 2 boiler reliability. A decade-long reliability profile was constructed and interpreted, along with average generation, plant availability, and related reliability indicators. A comparative analysis was used to interpret the results against world-class thermal power plant expectations, while recognising that local operating constraints, age, spares availability, and historical maintenance practices influence the achievable reliability envelope.

The third objective was to develop and test a boiler preventive maintenance strategy optimisation model. The dataset was prepared and analysed in Google Colab. Candidate algorithms included Random Forest Classifier, XGB Classifier, Logistic Regression, Logistic Regression CV, Decision Tree Classifier, K-Nearest Neighbours Classifier, Support Vector Classifier, and AdaBoost Classifier. Model performance was assessed using accuracy and related classification metrics. The best-performing algorithm was then used to build the preventive maintenance optimisation model.

The final objective validated the developed model. Model predictions for the first 16 weeks of 2024 were compared with actual HPS outcomes for the same period. Accuracy, precision, mean squared error, recall, and F1 score were used to assess validation performance. The developed predictive model was also deployed via a Streamlit web application so users could view predicted reliability and related performance outcomes, including maintenance costs, number of failures, plant availability, average boiler efficiency, and mean time between maintenance.

3.1. Data preparation and modelling logic

The monthly dataset was treated as an operational reliability record rather than as a purely statistical file. Before modelling, the variables were interpreted in engineering terms to ensure the model reflected practical boiler behaviour. Reliability, availability, and generation indicators were used to represent performance outcomes. Maintenance cost, number of failures, and mean time between maintenance were used to represent the burden and rhythm of maintenance activity. Boiler efficiency was retained because deterioration in efficiency may reveal underlying combustion, heat-transfer, or operating problems before complete functional failure occurs.

The modelling process followed a comparative algorithm approach. Each candidate algorithm was trained and evaluated on the same prepared dataset to ensure consistent performance comparison. Random Forest was retained because it offered a strong balance between predictive performance and interpretability. It is also robust in situations where the relationship between input variables and the target outcome is not linear. This is suitable for boiler maintenance because a small change in one factor may have little effect alone but becomes significant when combined with poor availability, recurring failures, or high maintenance costs.

The model was not designed to replace reliability engineering methods such as Weibull analysis. Rather, it complements them. Weibull-based models are valuable for failure distribution and life-data analysis, and modified Weibull approaches have been applied to power-system reliability forecasting [13]. The machine-learning model developed in this study is useful for linking historical operational variables to maintenance planning outcomes. By comparing the model outputs with established reliability thinking, the study strengthens confidence that the results are not merely a statistical artefact but a practical maintenance-planning signal.

3.2. Ethical and operational considerations

The study used plant-level operational and maintenance information for engineering analysis. No personal employee performance data were required for the model, and the results were interpreted at the system level. This is important because maintenance optimisation should improve the plant's reliability rather than create a blame culture around individual maintenance personnel. The value of the model depends on honest data capture and collaborative use by maintenance, operations, and planning teams.

Operationally, the model should be introduced through a controlled pilot rather than immediate full-scale dependence. During the pilot, the maintenance team should compare model outputs with engineering judgement, statutory inspection requirements, and outage planning constraints. This staged approach allows the plant to build confidence in the model, identify data-quality weaknesses and define clear rules for when model recommendations should trigger work orders, inspections or management review.

4. Results and Analysis

4.1. Effectiveness of the current maintenance strategy

The assessment shows that the current maintenance strategy at the Thermal Power Station Stage 2 is heavily biased toward corrective or reactive maintenance. Corrective maintenance accounts for approximately 72% of the maintenance approach, leaving only 28% distributed across preventive, predictive, and proactive work. This result is important because a high corrective share usually indicates that maintenance resources are being consumed after failure has already disrupted operation.

The interpretation of the maintenance cost curve supports the same conclusion. The plant is operating away from the desired reliability-cost balance, where planned work reduces total cost by preventing forced outages and secondary damage. In practical terms, the results imply that the maintenance department is spending a large share of its effort recovering from breakdowns rather than controlling the conditions that cause them. Table 1. gives the summary of maintenance strategies assessed at the power plant.

Table 1 Summary of the current maintenance strategy assessment.

Maintenance indicator	Observed position	Reliability implication
Corrective/reactive maintenance	About 72% of the strategy mix	High forced-outage exposure and unstable work planning
Preventive, predictive, and proactive maintenance	About 28% combined	Insufficient early intervention and condition-led planning
Cost-curve position	Biased toward a failure response	Total maintenance cost remains higher than the optimum zone

Figure 1 illustrates the plant availability based on the current maintenance strategies being utilized at the thermal power plant.

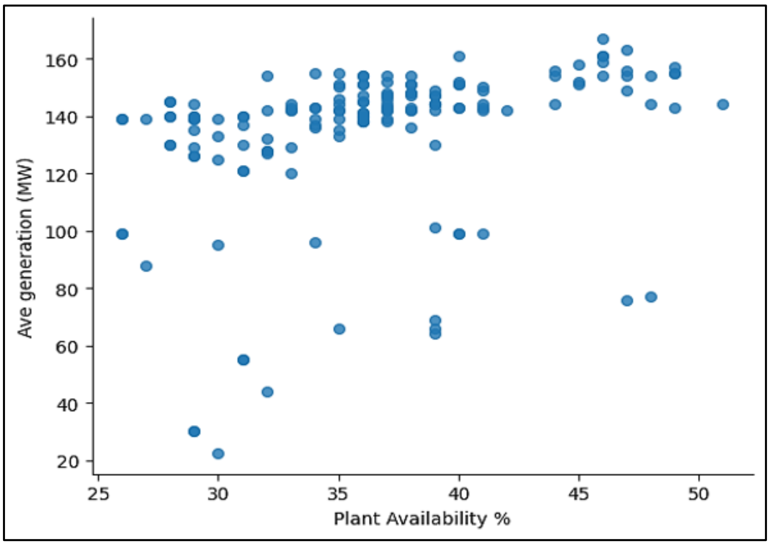

Figure 1 Plant availability trend

4.2. Boiler reliability profile

The Stage 2 boiler reliability profile was depressed during the period under review and fell short of world-class expectations for thermal power plants. The decade-long profile shows a gradual decline in reliability, confirming that the challenge is structural rather than a single-year anomaly. Reduced reliability was associated with lower availability and weaker average generation performance.

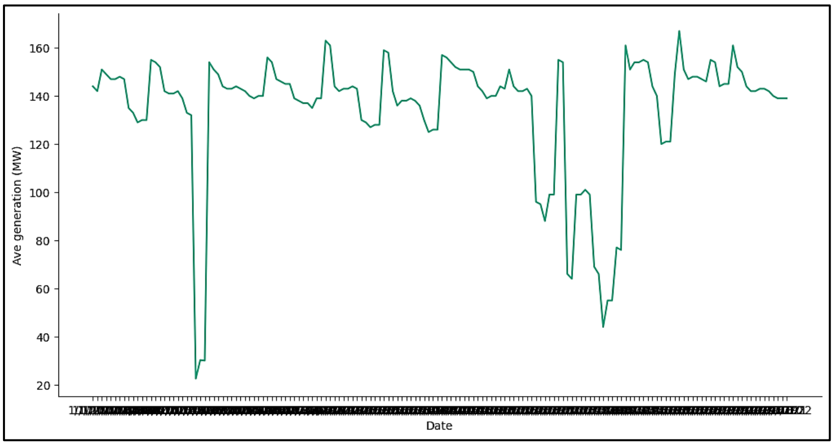

Figure 2 Decade-long boiler reliability profile

This result reinforces the need to move from a predominantly corrective maintenance posture to a planned, data-supported reliability strategy. A declining reliability trend also indicates that maintenance interventions should be prioritised according to failure mode criticality, recurrence, impact on generation, and the likelihood that timely intervention will restore performance. Figure 2 illustrates the boiler reliability profile over a period of ten years.

Figure 3. shows the boiler reliability and maintenance cost prediction tool based on the number of boiler failures.

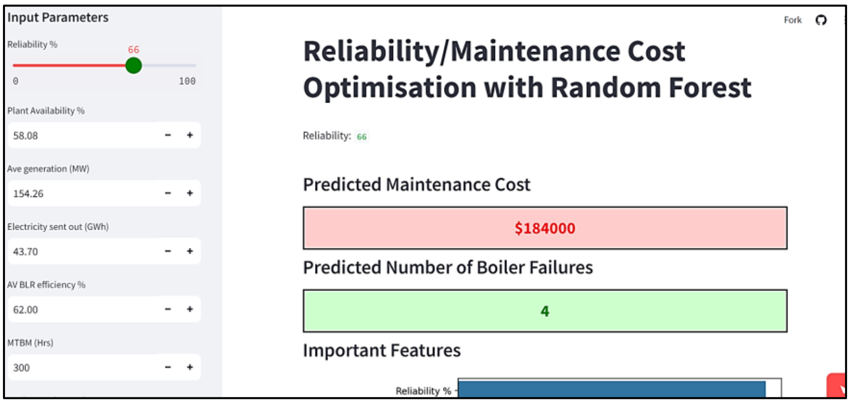

Figure 3 Boiler reliability and maintenance cost prediction

4.3. Development and testing of the preventive maintenance optimisation model

The model development phase evaluated several machine learning classifiers and selected Random Forest for the final preventive maintenance strategy optimisation model. The selection was based on comparative model performance and on the algorithm's suitability for multi-variable, non-linear maintenance data. The model was designed to identify the reliability point at which performance outcomes improve while predicted failures and maintenance costs decline.

The developed model identified an optimum reliability value of approximately 66%. At this point, plant availability was predicted at 58%, average generation at 154.26 MW, electricity sent out at 43.7 GWh, and mean time between maintenance at 300 hours as illustrated in Figure 4. The Predicted maintenance cost reduced to approximately USD 184,000, and the predicted number of boiler failures reduced to four. When the model was tested in the lower quartile reliability region at 25%, the predicted outcomes deteriorated: availability, average generation, and boiler efficiency declined, while maintenance costs increased to about USD 225,000, and predicted failures increased to 7.

These findings demonstrate the model's decision value. It does not merely classify the plant as reliable or unreliable; it shows how reliability is connected to operational and economic outcomes. This is important for maintenance managers because it translates a technical reliability target into a planning conversation about cost, failure exposure, generation output, and maintenance intervals.

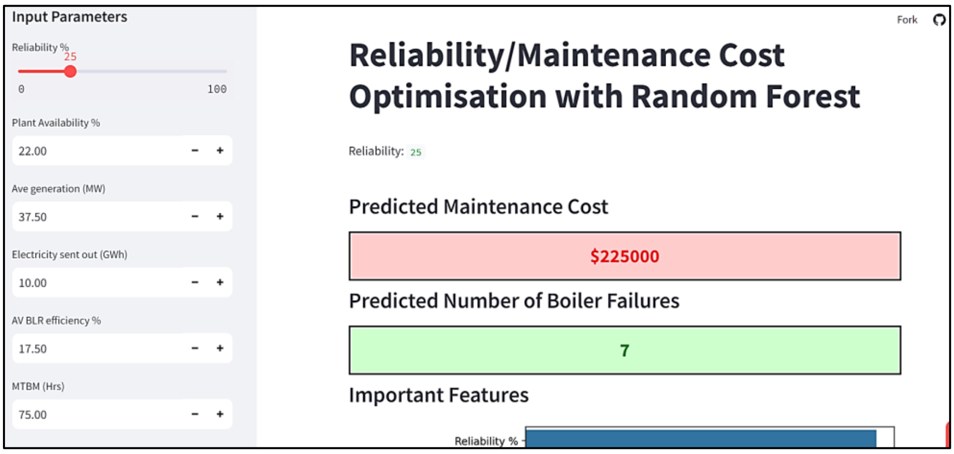

Figure 4 Model output at the optimum reliability region.

4.4. Validation of the developed model

Validation compared predicted outcomes with actual Stage 2 outcomes for the first 16 weeks of 2024. The validation results indicated good model performance across accuracy, precision, mean squared error, recall, and F1 score. The relationship between predicted and actual values was strongly positive, showing that the model captured meaningful patterns in the historical boiler maintenance and performance data.

However, the validation also showed that the actual 2024 performance remained below the model's optimum. This gap is expected because the developed preventive maintenance planning model had not yet been implemented as the operating maintenance strategy. The gap therefore has practical significance: it represents the improvement space that can be addressed if model recommendations are incorporated into maintenance planning, condition monitoring, spares planning, and weekly reliability review routines.

4.5. Comparison with reliability engineering expectations

The validation results were interpreted in relation to reliability engineering expectations. A conventional reliability model, such as a Weibull model, is useful for estimating failure behaviour and mean time between failures where life data are available. The developed Random Forest model provides a different but complementary form of insight. It estimates the reliability and performance outcomes associated with combinations of maintenance and operating variables. The comparison therefore suggests that the model is strongest as a planning and prioritisation tool rather than as a replacement for component-level failure analysis.

The practical advantage of the developed model is that it translates maintenance strategy into a set of visible performance outcomes. For example, the optimum region is not described only as a reliability percentage; it is associated with plant availability, average generation, electricity sent out, mean time between maintenance, maintenance cost and number of failures. This multi-output view is more useful for power-station management because budget decisions, outage planning and generation commitments are made across several performance indicators at once.

The results also confirm that reliability improvement cannot be achieved solely through model deployment. The current gap between actual outcomes and model-optimised values indicates that the plant must revise its work management process to align with the model. In particular, the model should influence preventive work order generation, shutdown preparation, spares prioritisation, inspection intervals, and post-maintenance review. Without these operational links, the model will describe an optimum that the station does not consistently pursue.

5. Discussion

The results show that improving boiler reliability at the Thermal Power Station Stage 2 requires both technical and managerial changes. The technical change is the use of data to identify reliability-sensitive operating regions, failure exposure, and maintenance timing. The managerial change is the discipline to move maintenance work from a reactive schedule to a planned reliability programme. Without the second change, even a well-performing machine-learning model will remain a useful dashboard rather than an operational improvement tool.

A key strength of the developed approach is that it is tailored to coal-fired power station conditions rather than imported as a generic manufacturing maintenance model. Boiler performance is affected by plant age, coal quality, operating load, start-stop patterns, availability of spares, water chemistry, combustion conditions, and maintenance backlog. A locally trained model based on the plant's historical data is therefore more useful than a purely theoretical maintenance interval.

The study also shows that machine learning should be treated as decision support. The Random Forest model can identify patterns and estimate outcomes, but the final maintenance decision must still consider safety, statutory inspection requirements, equipment criticality, resource availability and engineering judgement. The best use of the model is to improve weekly and monthly maintenance planning, prioritise high-risk boiler components, justify preventive interventions, and provide early warning when performance is moving away from the optimum region.

From a policy and energy security perspective, the study is relevant beyond a single power station. Many African coal-fired plants operate under resource constraints, aging assets, and demand pressure. A practical preventive maintenance optimisation model can help such plants reduce forced outages, improve sent-out energy, and protect scarce maintenance budgets. The approach is therefore not only an engineering tool but also a contribution to reliability-centred electricity supply management.

5.1. Implementation pathway for the Thermal Power Station

For the model to produce a measurable value at the Thermal Power Station, it should be embedded in the existing maintenance planning cycle. A practical implementation pathway begins with a pilot on the Stage 2 boilers. During the pilot, the model should be run at a fixed planning interval, preferably weekly or monthly, using updated reliability and maintenance data. Its outputs should be reviewed by a joint team comprising maintenance engineers, operations personnel, planners, and reliability engineers. The team should record whether the model recommendation was accepted, modified, or deferred, and why.

The second step is to connect model outputs to the computerised maintenance management system. Work orders should not be generated automatically without engineering review, but high-risk model outputs should trigger inspection tasks, spares checks or focused condition monitoring. Over time, this will create a feedback loop in which model predictions, engineering actions, and actual outcomes are captured in the same data environment. This feedback loop is essential for continuous improvement because it allows the model to learn from new plant behaviour and allows engineers to evaluate whether preventive interventions are reducing failure recurrence.

The third step is governance. Management should define reliability thresholds, escalation rules, and reporting responsibilities. For example, if predicted reliability moves below an agreed threshold, the system should require a maintenance review meeting, a failure-mode check, and a short-term action plan. If predicted maintenance cost rises while availability falls, the issue should be escalated as a reliability risk rather than treated as a routine cost variance. These governance rules turn the model from a technical experiment into a management tool.

5.2. Limitations of the study

The study has limitations that should guide interpretation of the results. First, the model was developed from historical monthly data for a single power station stage. Although the time horizon is substantial, monthly data may smooth short-term events such as rapid tube leaks, forced outages, abnormal start-up conditions, or short-duration control problems. Higher-frequency data from sensors and the distributed control system could improve the sensitivity of future models.

Second, the model was validated against the first 16 weeks of 2024, but it was not tested through a full live implementation cycle in which model recommendations were used to plan maintenance and then measured against subsequent outcomes. This means that the study validates predictive behaviour, while implementation impact still needs to be demonstrated through a controlled operational pilot.

Third, the model does not fully incorporate external constraints such as coal quality variation, water chemistry excursions, delayed spares procurement, capital funding limits, statutory outage requirements, and opportunity cost of downtime. These factors can influence maintenance decisions even when the model identifies a technically desirable reliability outcome. Future work should integrate these constraints to enable the model to support both technical and economic optimisation.

Recommendations

- Implement the developed preventive maintenance strategy optimisation model at the Thermal Power Station Stage 2 as a decision-support tool for boiler maintenance planning.
- Create a reliability review routine in which model predictions are compared with weekly plant outcomes, including boiler failures, availability, average generation, maintenance cost and mean time between maintenance.
- Strengthen condition monitoring by linking inspection records, operating data, boiler efficiency data and maintenance history into one controlled dataset for model updating.
- Use model outputs to prioritise preventive work orders, spares planning and outage preparation for high-risk boiler components.
- Conduct a formal cost-benefit analysis after pilot implementation to quantify avoided failures, reduced maintenance cost, improved availability, and additional sent-out energy.
- Retrain and validate the model periodically so that it remains aligned with changing plant conditions, maintenance practice and operating regimes.

6. Conclusion

This paper improved and consolidated a study on the impact of the preventive maintenance strategy on boiler reliability at the Thermal Power Station Stage 2. The evidence shows that the existing maintenance strategy is dominated by corrective maintenance, accounting for about 72% of the strategy mix. The maintenance strategy has contributed to depressed boiler reliability, reduced plant availability, and avoidable maintenance cost exposure.

Using a 13-year monthly dataset, the study developed and validated a random forest-based model for optimising preventive maintenance strategies. The model identified an optimum reliability region of about 66%, linked to improved availability, average generation, sent-out energy, mean time between maintenance, and reduced predicted failures and maintenance costs. Validation against 2024 data showed a strong positive relationship between predicted and actual outcomes, while also revealing the improvement gap resulting from the non-implementation of the model.

The study concludes that a machine-learning-enabled preventive maintenance strategy can materially strengthen boiler reliability planning in coal-fired power stations. For the Thermal Power Station, the next step is operational integration: the model should be embedded into maintenance planning, condition monitoring, spares provision, and management review so that predictive insight becomes measurable reliability improvement.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there are no financial or personal relationships that could have inappropriately influenced the research, analysis, or interpretation presented in this paper.

Statement of ethical approval

The present research work does not contain any studies performed on animal or human subjects by any of the authors. The study relied on plant-level operational and maintenance data from the Thermal Power Station Stage 2, and no individual employee performance data were used.

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