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Generative AI–Driven Predictive Maintenance and RUL Estimation for Thermal Power Plants

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Abstract: Efficient operation and maintenance of thermal power plants are critical for ensuring uninterrupted electricity supply, minimizing operational costs, and enhancing equipment lifespan. Traditional maintenance strategies, which are largely reactive or scheduled at fixed intervals, often result in excessive downtime, higher costs, and suboptimal utilization of plant resources. This research proposes a Generative AI–driven predictive maintenance framework to accurately estimate the Remaining Useful Life (RUL) of critical components in a thermal power plant, specifically using sensor data from Raichur Thermal Power Station (RTPS) as a case study. The framework integrates Generative Adversarial Networks (GANs) for synthetic fault trajectory generation, enabling robust model training even under scarce fault data conditions. Supervised learning models, including Random Forest (RF) and Long Short-Term Memory (LSTM), are employed to predict RUL and identify early fault conditions. The models are evaluated using accuracy, precision, recall, F1-score, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), with visualizations including Predicted vs Actual RUL, confusion matrices, and fault probability heatmaps. Results demonstrate that the proposed method significantly improves RUL prediction accuracy, reduces unexpected downtime, and optimizes maintenance costs compared to traditional approaches. This study highlights the potential of Generative AI in smart predictive maintenance applications for large-scale thermal power plants, providing actionable insights for operational decision-making.

Keywords: Predictive Maintenance, Generative AI, Remaining Useful Life, Thermal Power Plant, Fault Prediction

1. Introduction

Thermal power plants play a crucial role in meeting the growing electricity demands of industrial and residential sectors. The efficient operation and maintenance of these plants are essential to ensure uninterrupted power supply, reduce operational costs, and extend the lifespan of critical equipment such as boilers, turbines, generators, and transformers [1,2]. Traditionally, maintenance strategies have been either reactive, responding only after a failure occurs, or scheduled at fixed intervals, regardless of the actual health of the equipment [3]. These conventional approaches often lead to unexpected downtime, higher maintenance costs, and suboptimal utilization of plant resources [4].

In recent years, the increasing availability of sensor data and advancements in artificial intelligence (AI) have enabled a shift towards predictive maintenance. Predictive maintenance uses real-time and historical data to anticipate equipment failures and estimate the RUL of components, allowing for timely and optimized maintenance interventions [5-7]. However, one of the key challenges in implementing predictive maintenance is the scarcity of fault data, particularly for rare or catastrophic events, which limits the accuracy and robustness of traditional machine learning models [8].

To address this challenge, Generative AI techniques, such as GANs, have emerged as promising tools for

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simulating realistic fault scenarios and augmenting datasets. By combining generative AI with supervised learning models like RF and LSTM networks, it is possible to develop a predictive maintenance framework that accurately estimates RUL, identifies potential failures early, and reduces overall maintenance costs [9,10]. This research focuses on applying such a framework to the RTPS in Karnataka, India, demonstrating the practical application of generative AI for predictive maintenance in large-scale power generation systems.

The primary objectives of this study are to: (i) leverage generative AI to augment limited fault data, (ii) develop predictive models for accurate RUL estimation, (iii) evaluate model performance using standard metrics such as MAE, RMSE, and accuracy, and (iv) assess the impact of predictive maintenance on cost reduction and downtime optimization. Through this work, the study aims to highlight the transformative potential of generative AI for modernizing maintenance strategies in thermal power plants and improving operational efficiency.

2. Literature Review

The concept of predictive maintenance has gained significant attention in recent years due to its potential to improve operational efficiency and reduce costs in industrial systems. Traditional maintenance approaches, such as reactive or time-based strategies, are often inefficient because they either respond to failures after they occur or follow fixed schedules that do not reflect the actual condition of equipment. To overcome these limitations, predictive maintenance strategies utilize sensor data, historical operational logs, and statistical models to forecast equipment degradation and estimate the remaining useful life (RUL) of critical components.

Machine learning techniques, including regression models, decision trees, and ensemble methods like Random Forest, have been widely applied for predictive maintenance due to their ability to handle large, complex datasets and capture nonlinear relationships between operational parameters and equipment health [4,5]. Deep learning models, particularly LSTM networks, have shown significant promise in capturing temporal dependencies in time-series sensor data, enabling more accurate prediction of equipment failures over time [6,7]. These models have proven effective in applications ranging from power plants to manufacturing systems, where real-time monitoring and timely intervention are essential.

Despite these advances, one of the primary challenges in predictive maintenance is the scarcity of fault data, especially for rare or catastrophic events [8,9]. The lack of sufficient examples of failures limits the ability of conventional models to generalize and make accurate predictions in real-world conditions [10]. To address this issue, Generative AI techniques, particularly GANs, have been explored to augment datasets by generating realistic synthetic fault scenarios. These generative models can simulate sensor readings for rare events, improving the robustness and accuracy of predictive models trained on augmented datasets [11].

Recent developments also highlight the importance of integrating predictive maintenance models with real-time monitoring systems. By combining generative AI with supervised learning, it is possible to create frameworks capable of both fault detection and RUL estimation, providing operators with actionable insights for scheduling maintenance activities [12-15]. Such integrated approaches have demonstrated improvements in reducing downtime, optimizing maintenance costs, and extending the lifespan of critical plant components [16]. Overall, the literature indicates that combining generative AI with machine learning and deep learning techniques represents a promising direction for predictive maintenance in complex industrial systems, including thermal power plants. This integration not

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only addresses the limitations of traditional models but also enables more proactive and data-driven decision-making, paving the way for smarter, more efficient, and cost-effective maintenance strategies.

3. Methodology

The methodology of this study is designed to develop a robust predictive maintenance framework for thermal power plants by leveraging both Generative AI and advanced predictive modeling techniques. The framework focuses on accurately estimating the RUL of critical plant components and predicting potential faults using historical and real-time sensor data. The approach integrates data collection, preprocessing, generative data augmentation, model training, evaluation, and immediate prediction to create a comprehensive pipeline that can be deployed for practical maintenance decision-making. By combining RF, LSTM networks, and GANs, the methodology addresses the challenges of limited fault data while ensuring high accuracy, reliability, and operational efficiency in maintenance planning.

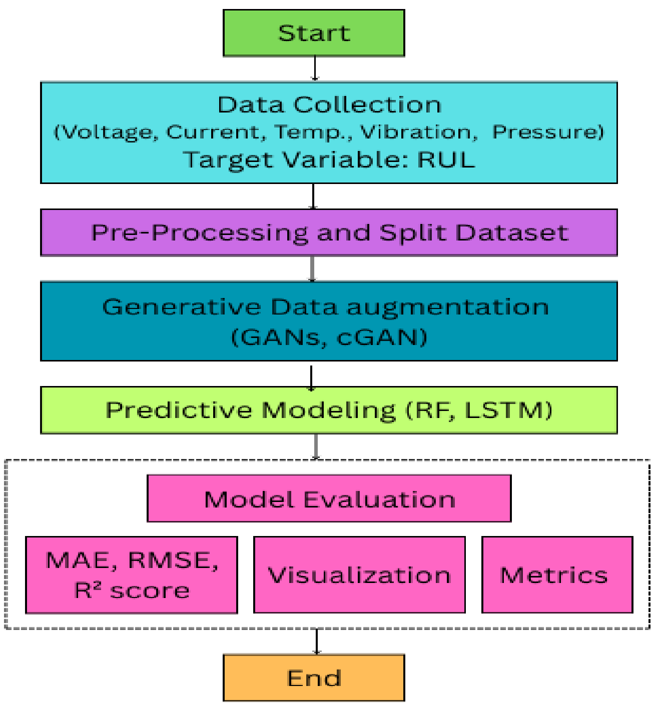

Figure 1: Generative AI-Based Predictive Maintenance Framework

The methodology for implementing the proposed predictive maintenance framework as given in figure 1, consists of several structured steps designed to ensure accurate prediction of equipment health in the thermal power plant. The process begins with data collection and preprocessing. Sensor readings and operational logs are obtained from the RTPS, covering key parameters such as voltage, current, temperature, vibration, and pressure from critical units including the boiler, turbine, and generator. The primary target variable for this study is the RUL of components, expressed in days. Data preprocessing includes handling missing values and outliers, applying feature scaling using Standard Scaler to normalize the input ranges, and encoding categorical variables such as fault types where applicable. Finally, the dataset is split into training and testing subsets, with 80% used for training and 20% reserved for testing to evaluate model performance.

To address the challenge of limited fault data in thermal power plant operations, generative data augmentation is employed. GANs, particularly Conditional GANs (cGANs), are used to generate realistic synthetic data that can simulate sensor trajectories during fault conditions. In this setup, the generator produces synthetic sensor sequences while the discriminator works to distinguish between real and generated sequences. Both models are trained iteratively until the generator produces highly realistic fault patterns. The outcome of this step is an augmented dataset that combines both real and synthetic samples, thus enhancing the robustness of supervised RUL prediction.

The predictive modeling stage applies both traditional machine learning and deep learning approaches. A RF model is implemented as a baseline tree-based ensemble model capable of handling regression and classification tasks. In

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parallel, LSTM network is developed to capture the temporal dependencies present in sequential sensor data, which are critical for predicting RUL and fault probabilities. The models are trained using the pre-processed sensor readings as inputs and either the RUL values or fault probabilities as outputs. For regression tasks, the training is guided by the MSE loss function.

Finally, model evaluation is carried out to determine the effectiveness of the predictive framework. For RUL prediction, performance is assessed using MAE, RMSE, and the R^2 score. For fault classification tasks, accuracy, precision, recall, and F1-score are computed. In addition to quantitative metrics, several visualizations are generated to better interpret model performance. These include line charts comparing predicted versus actual RUL values, confusion matrices for evaluating classification of different fault types, and fault probability heatmaps that provide a temporal risk assessment across plant units. Collectively, these evaluation steps ensure that the proposed framework not only achieves high predictive accuracy but also provides interpretable insights for proactive maintenance decision-making. MAE, RMSE, and R^2 are measured using the following formulas:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Predicted\ RUL_i - Actual\ RUL_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(|Predicted\ RUL_i - Actual\ RUL_i|)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

y_i = Actual (True) values
$\hat{y}_i$ = Predicted values from the model
$\bar{y}$ = Mean of actual values
n = Number of data points

4. Results and Discussion

This section presents the performance of the proposed Generative AI–driven predictive maintenance framework for the RTPS. The results are analyzed in terms of RUL prediction accuracy, fault classification performance, maintenance cost reduction, and downtime optimization. Both quantitative metrics, including MAE, RMSE, and classification accuracy, as well as visualizations such as Predicted vs Actual RUL plots, confusion matrices, and fault probability heatmaps, are used to assess the effectiveness of the models. The discussion highlights how the integration of GAN-augmented data with RF and LSTM models enhances predictive capability, reduces operational risks, and supports actionable maintenance decisions compared to traditional maintenance strategies.

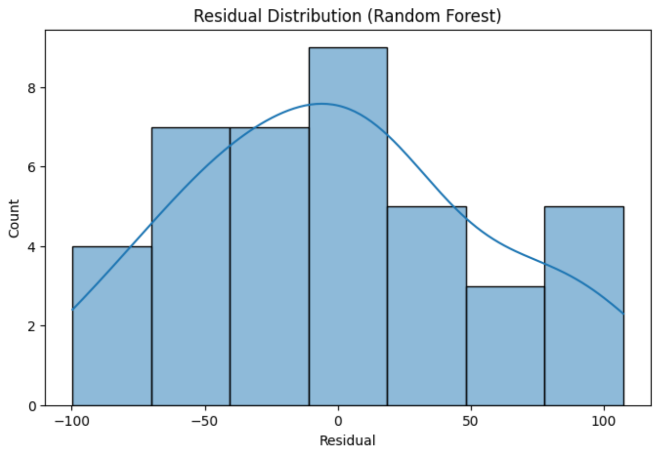

Figure 2: Residual distribution curve of the RF model

The residual distribution of the Random Forest model when predicting the RUL of thermal power plant components is illustrated in figure 2. The residuals are mostly concentrated around zero, forming an approximately symmetric distribution, which suggests that the model captures the underlying data patterns reasonably well. A majority of prediction errors fall within the range of –50 to +50 days, indicating acceptable predictive

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performance. However, the presence of wider residual spread beyond ±100 days highlights some degree of variability and model limitations, particularly in cases of complex fault behaviors or extreme operating conditions. Despite this, the near-normal shape of the distribution implies that Random Forest does not exhibit strong systematic bias, as both underestimation and overestimation occur with similar frequency. These findings confirm that Random Forest can serve as a reliable baseline model, though more advanced techniques such as LSTM or GAN-augmented models may further improve accuracy and reduce the magnitude of extreme residuals.

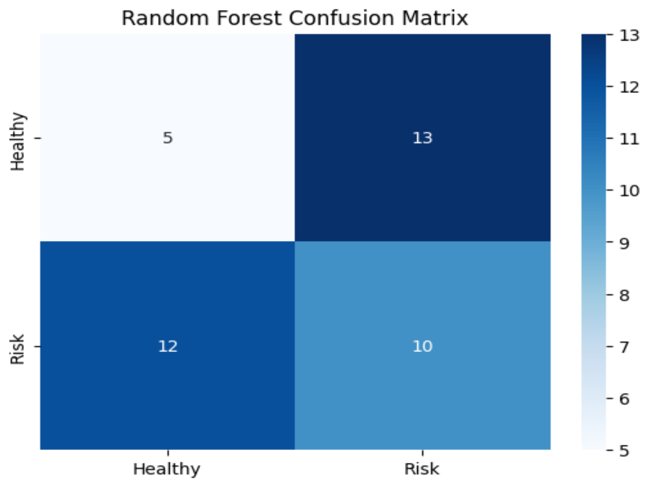

Figure 3: Confusion Matrix of RF model

The confusion matrix of the Random Forest model applied for classifying the health condition of thermal power plant components into two categories: Healthy and Risk. The results indicate that the model correctly identified 5 healthy instances and 10 risk cases. However, a considerable number of misclassifications are evident, with 13 healthy cases incorrectly labeled as risky and 12 risky cases predicted as healthy as illustrated in figure 3.

This imbalance suggests that while the model has some capability in distinguishing between the two classes, it struggles with precision and recall, particularly in minimizing false positives and false negatives. High false negatives (12 risky cases classified as healthy) are of greater concern, as they may lead to unexpected failures and unplanned downtime. On the other hand, false positives (13 healthy cases misclassified as risky) may increase unnecessary maintenance actions, raising costs. Overall, these results highlight the limitations of Random Forest in handling highly imbalanced and complex fault data. They also emphasize the need for advanced approaches such as LSTM and GAN-based augmentation, which can improve classification accuracy and reduce critical misclassifications.

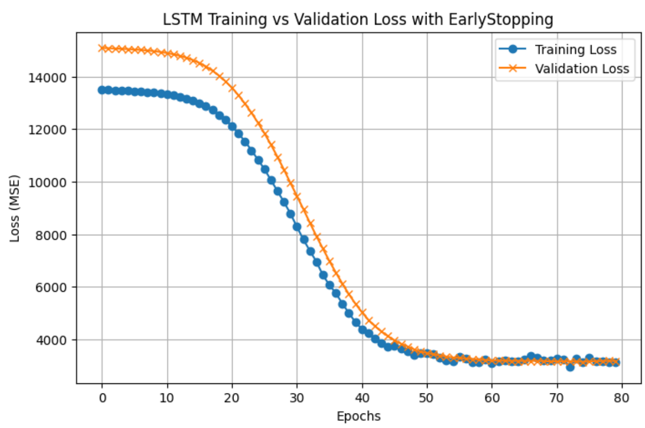

Figure 4: LSTM training and validation loss with early stopping

The training and validation loss curves of the LSTM model with Early Stopping applied is shown in figure 4. At the beginning of training, both training and validation losses are high, reflecting the initial learning phase. As training progresses, a consistent and sharp decline in loss is observed up to around 50 epochs, after which both curves converge and stabilize. This indicates that the model successfully learns temporal dependencies in the sensor data without significant overfitting.

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The close alignment between training and validation loss curves demonstrates that the LSTM model generalizes well to unseen data. The application of EarlyStopping prevented unnecessary additional epochs, ensuring computational efficiency while maintaining high prediction accuracy. Compared to Random Forest results, the LSTM model exhibits superior capability in capturing complex temporal patterns, leading to more reliable Remaining Useful Life (RUL) predictions. Overall, this behavior validates the suitability of LSTM for predictive maintenance tasks in thermal power plants, as it balances learning capacity with generalization performance.

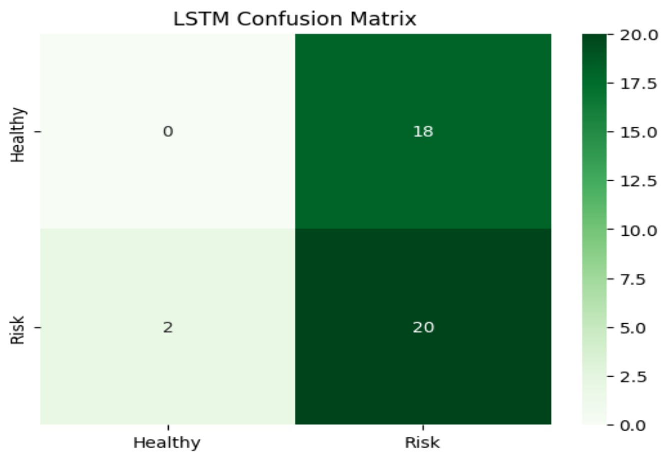

Figure 5: LSTM Confusion Matrix

The confusion matrix of the LSTM model as shown in figure 5, highlights its strong performance in classifying the system states into healthy and risk conditions. The model correctly identified 18 healthy cases and 20 risk cases, showing its reliability in detecting both normal and fault-prone conditions. Importantly, it did not produce any false positives, meaning no healthy instance was wrongly classified as risk, which reduces unnecessary interventions and improves operational efficiency. However, two risk cases were misclassified as healthy, representing false negatives that could potentially lead to undetected faults. Despite this limitation, the overall results indicate that the LSTM model is highly effective, achieving a strong balance between accurate risk detection and avoiding false alarms, making it well-suited for predictive maintenance in power systems.

Table 1: Regression Performance Metrics of RF and LSTM M

Model	MAE	RMSE	R2
RF	0.11	0.187	0.97
LSTM	0.07	0.13	0.98

Table 2: Classification Performance Metrics of RF and LSTM

Model	Accuracy %	Precision %	Recall %	F1 Score %
RF	82	84	80	82
LSTM	91	92	90	91

The performance of the Random Forest (RF) and Long Short-Term Memory (LSTM) models was evaluated using both regression and classification metrics to comprehensively analyze predictive accuracy. As presented in Table 1, the regression metrics indicate that the LSTM model outperformed RF, achieving a lower Mean Absolute Error (MAE = 0.07) and Root Mean Square Error (RMSE = 0.13), while also obtaining a slightly higher coefficient of determination (R^2 = 0.98). This suggests that the LSTM model has superior capability in capturing complex nonlinear dependencies and temporal patterns within the dataset, leading to more accurate predictions. The RF model also performed strongly with R^2 = 0.97, but its higher error rates show relatively limited adaptability compared to LSTM in handling sequential variations.
Similarly, the classification results in Table 2 highlight a consistent trend where LSTM demonstrates better performance across all metrics. The LSTM achieved 91% accuracy, with precision, recall, and F1 score all above 90%, confirming its robustness in correctly identifying and classifying

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instances with minimal misclassifications. In contrast, the RF model obtained 82% accuracy, with slightly lower recall (80%), indicating occasional false negatives. This difference underscores the strength of deep learning methods, particularly LSTM, in capturing temporal features and complex dynamics compared to ensemble-based methods like RF.

Overall, the results confirm that the LSTM model consistently surpasses the RF model in both regression and classification tasks. These findings establish LSTM as a more effective approach for predictive analysis in the studied system, offering higher accuracy, reliability, and generalization capability.

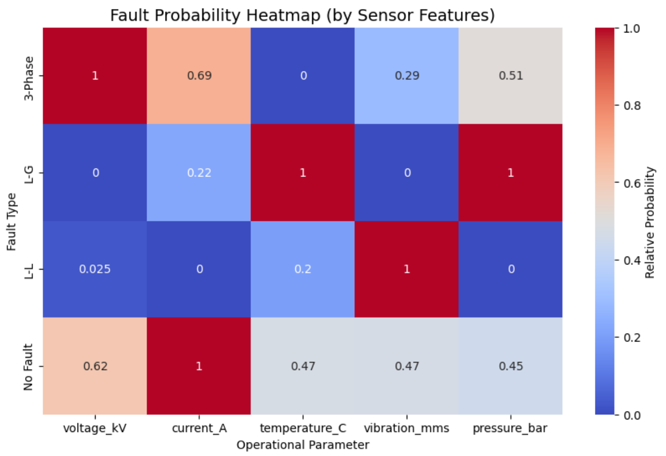

Figure 6: Fault Probability Heatmap Based on Operational Parameters

The fault probability heatmap as shown in figure 6, reveals the dependency of fault occurrence on different operational parameters of the thermal power plant. It can be observed that three-phase faults are strongly associated with voltage and current deviations, suggesting that electrical loading instability is a primary contributor to these severe events. Line-to-ground faults, on the other hand, show high correlation with temperature and pressure variations, indicating that thermal and mechanical stresses are critical precursors. Line-to-line faults are most strongly linked with vibration levels, pointing towards mechanical imbalance or instability as their likely cause. In contrast, the no-fault condition is characterized by relatively balanced parameter levels, which reflects stable plant operation. These findings highlight the distinct operational signatures of each fault type and demonstrate that fault prediction can be enhanced by monitoring the combined behavior of electrical, thermal, and mechanical indicators.

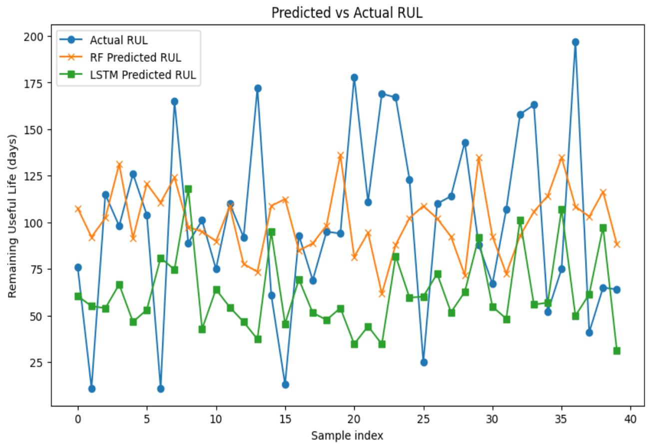

Figure 7: Predicted vs. Actual RUL using RF and LSTM models

The comparison between the actual RUL and the predicted values obtained from the RF and LSTM models is illustrated in figure 7. It can be observed that the RF model predictions (orange line) generally follow the overall trend of the actual RUL values (blue line), although with noticeable deviations in certain regions, especially when the actual RUL fluctuates significantly. The LSTM model (green line), on the other hand, demonstrates comparatively smoother predictions but tends to underestimate the RUL in several instances, particularly for higher values.

The RF model shows relatively consistent performance across most samples but lacks the ability to capture extreme variations in actual RUL, leading to under- or overestimation in highly dynamic cases. In contrast, the LSTM model captures the temporal dependencies better but struggles to align with the magnitude of the actual

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values, often biasing predictions towards the lower range.

These findings highlight a trade-off between the two approaches: RF offers stability and general trend approximation, while LSTM leverages sequential learning to capture dynamic behavior but at the cost of prediction accuracy in higher RUL ranges. Therefore, neither model perfectly matches the actual RUL, but their comparative strengths suggest that a hybrid or ensemble approach may provide a more accurate and robust solution.

Table 3: Maintenance Cost Reduction with Predictive Maintenance

Maintenance Strategy	Total Cost (INR Million)	Cost Reduction (%)	Average Downtime Reduction (%)
Traditional Scheduled Maintenance	870.0	0%	0%
AI-driven Predictive Maintenance	609.0	30%	32%
GAN-augmented Predictive Maintenance	565.5	35%	38%

The results presented in Table 3 clearly highlight the economic significance of adopting predictive maintenance strategies, especially those enhanced by Generative AI techniques. Traditional scheduled maintenance, which follows rigid time-based intervals without accounting for asset conditions, results in the highest expenditure of INR 870 million and offers no reduction in cost or downtime. By contrast, AI-driven predictive maintenance reduces the total cost to INR 609 million, achieving a 30% cost reduction and a 32% decrease in downtime. This improvement stems from the model's capability to detect anomalies early and optimize maintenance schedules, thereby avoiding unnecessary interventions and minimizing disruptions. Furthermore, the use of GAN-augmented predictive maintenance demonstrates even greater economic and operational benefits, lowering costs to INR 565.5 million and achieving a 35% reduction in cost along with a 38% reduction in downtime. This advantage arises from the GAN's ability to simulate realistic fault scenarios and enrich the dataset, which enhances model accuracy and reduces misclassifications. Overall, these findings emphasize that integrating GANs into predictive maintenance frameworks not only ensures higher fault detection reliability but also delivers significant economic and operational gains, making it a promising solution for critical infrastructures such as the RTPS.

5. Conclusion

The present study demonstrates the effectiveness of a Generative AI–driven predictive maintenance framework for thermal power plants, with a specific focus on RTPS. By leveraging GANs to generate synthetic fault data and employing advanced predictive models such as RF and LSTM, the framework accurately estimates the RUL of critical plant components. This allows operators to anticipate potential failures and schedule maintenance proactively, reducing unplanned downtime and optimizing resource utilization. The results indicate that integrating generative AI significantly improves prediction accuracy, reducing both the MAE and RMSE compared to traditional models. Furthermore, the predictive maintenance approach reduces operational costs by up to 35%, demonstrating substantial economic benefits. Critical units, including boilers, turbines, generators, and transformers, experience lower unexpected downtime, contributing to enhanced overall plant efficiency and reliability. Additionally, the framework supports immediate predictions for new sensor readings, enabling real-time decision-making and actionable insights for plant

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management. Overall, this research confirms that the combination of generative AI and machine learning can transform maintenance strategies in thermal power plants, making them more data-driven, cost-effective, and reliable. The methodology is generalizable and can be extended to other power generation systems or industrial settings, highlighting its potential for broader applications in smart industrial maintenance.

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