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Analyzing Power Plant Data Using Artificial Intelligence to Enhance Maintenance Strategy

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ABSTRACT

This research aims to optimize maintenance strategies in power plants by leveraging artificial intelligence (AI) techniques to analyze historical operational data. The study adopts a quantitative analytical approach, utilizing deep learning algorithms—including GRU, LSTM, and TCN—to detect anomalies and predict equipment malfunctions. Historical data from a power plant, encompassing sensor readings, fault logs, and operational parameters, were collected, pre-processed, and analyzed. The results demonstrate that the GRU algorithm outperforms other models, achieving an accuracy exceeding 83% and the lowest loss value, thereby proving its robustness in generalization and predictive capability. The proposed system significantly reduces unplanned downtime, minimizes maintenance costs, and enhances operational efficiency. A practical case study confirms the effectiveness of the approach in real-world settings. The integration of AI into power plant maintenance not only improves system reliability but also supports sustainability objectives, establishing AI-driven predictive maintenance as a strategic asset for the modern energy sector.

Introduction

The energy sector is undergoing a paradigm shift driven by advancements in artificial intelligence and big data analytics. Power plants generate vast amounts of operational data from sensors and monitoring systems, offering unprecedented opportunities to optimize maintenance strategies and improve efficiency [1]. Traditional maintenance approaches often result in unplanned downtime and high costs, highlighting the need for more proactive and data-driven solutions. Artificial intelligence technologies, such as machine learning and predictive analysis, make it possible to monitor equipment performance and predict possible malfunctions before they occur, reducing unplanned downtime and reducing maintenance costs [2]. Modern power plants rely on huge amounts of data collected from sensors and monitoring systems, which provides an opportunity to use artificial intelligence in analyzing this data to detect patterns, predict malfunctions, and optimize maintenance strategies [3,4] .

This study addresses the critical challenge of enhancing maintenance strategies in power plants by integrating AI-based predictive analytics. While previous research has explored the use of machine learning for maintenance optimization, gaps remain in the practical deployment of deep learning models for anomaly detection and predictive maintenance in real-world industrial settings. Our research aims to bridge this gap by developing and validating a robust AI-driven framework for power plant maintenance.

The adoption of AI in maintenance not only reduces operational disruptions and costs but also supports environmental sustainability by minimizing resource waste and emissions. However, challenges such as data processing efficiency, model accuracy, and data security must be addressed to realize the full potential of these technologies [5]. Through the use of predictive analysis and Big Data, significant improvements in maintenance and operation can be achieved, contributing to the achievement of efficiency and sustainability goals in the energy sector[6]**.** This study contributes to the field by providing a comprehensive methodology and practical validation of AI-driven maintenance strategies.

1. Literature Review

Recent studies have demonstrated the transformative impact of AI on energy system maintenance. In 2024 Li et al[7]. developed quadratic models for geothermal energy systems, achieving superior predictive accuracy compared to linear models. Gong et al[8]. in 2024 highlighted the importance of AI-based fault detection in nuclear plants, emphasizing the limitations of traditional mathematical models. In 2025, Lin et al[9]. explored predictive maintenance in nuclear plants using explainable AI, addressing transparency challenges in machine learning models. Underscored Chiacchio et al[10]. in 2024 the significance of high-quality training data and proposed dynamic reliability digital twins for data augmentation. Asghar et al[11]. in 2023 demonstrated the effectiveness of neural networks in predicting power plant performance, while Nabil et al[12]. in 2024, achieved high accuracy in predictive maintenance using hybrid deep learning and multi-agent systems. Zhang et al.[13] in 2023 introduced a federated learning framework for distributed energy systems, enhancing privacy-preserving predictive analytics. Moreover, Hassan et al.[14] in 2024 applied convolutional neural networks (CNNs) for thermal anomaly detection in solar farms, achieving real-time diagnostic capability. Finally, Kumar et al.[15] in 2025 proposed a reinforcement learning approach to optimize maintenance scheduling in wind turbines, reducing operational costs and improving system reliabilityA comparative analysis of these studies is presented in Table 1, highlighting the methodologies, key findings, and relevance to our research**.**

2. The Methodology

This paper was based on a quantitative analytical methodology based on artificial intelligence techniques to analyze power plant data, with the aim of developing a more effective maintenance strategy. The methodology includes the following stages,

2.1 Data Collection

Historical operational data were collected from the Kirkuk power plant. The number of readings in the data set was 4380 readings taken during the period from 1/1/2024 to 1/12/2024. The dataset was split into 70% for training, 15% for testing, and 15% for validation with performance evaluated using accuracy and loss metrics.

2.2 Data Preprocessing

The data used in this study was collected from manual logs recorded every two hours by technicians, with readings for each variable recorded separately. This data was then manually entered into Excel spreadsheets to organize it and facilitate processing. The preprocessing phase included cleaning the data of missing or invalid values, standardizing units, and segmenting the data into consistent time intervals to ensure data quality before using it in the application of artificial intelligence algorithms.

The sensor readings included the following variables: fuel gas supply, fuel gas system, GT lube/lift oil system, GT hydraulic system, GT turbine VIB/Temp, GT generator VIB/Temp, and GT burner temp MOH. These variables were selected because of their direct correlation to gas turbine performance and subsystem safety. They reflect any abnormal changes in fuel supply, lubrication systems, temperatures, and vibrations, contributing to the early detection of potential failures and avoiding unplanned downtime. These variables are key indicators in proactive maintenance because they provide a comprehensive view of equipment condition and enable corrective action before problems escalate.

Table 2 summarizes the main features used in this study, highlighting the number of monitored variables, considerations regarding faulty versus normal data, and the defined operational thresholds for each parameter. This detailed summary supports a better understanding of the data quality and the boundaries applied during anomaly detection and predictive maintenance model development.

Table 3 represents a list of the main sensors ’readings that were used in research with its natural operational limits, warnings and fault borders. These values were obtained from the station's operational documents. The table for each variable (such as gas pressure, oil temperature, turbine speed, etc.) shows the acceptable natural values, and warning values (when reading approaches out of the normal range), and the values of faults (when reading exceeds the maximum or worldly limits).

Table 1: Comparative Analysis of Related Works

Study (Year)	Methodology	Key Findings/ Contribution	Relevance to Current Study
Li et al. (2024)	Quadratic models	R^2=99.88% for quadratic model	Predictive accuracy
Gong et al. (2024)	AI-based FDD	Overcomes limitations of traditional FDD	Fault detection
Lin et al. (2025)	Explainable AI, ML	Enhances model transparency	Interpretability
Chiacchio et al. (2024)	Digital Twin, ML	Improves data quality	Data augmentation
Asghar et al. (2023)	BPNN, Thermodynamics	High predictive accuracy	Performance prediction
Nabil et al. (2024)	LSTM, MAS	97% accuracy, predicts failures	Predictive maintenance

Table 2: Summary of Monitored Features, Faulty Data Ratio, and Operational Thresholds

Item	Details
Number of features	7 key features were measured: 1. Natural gas supply pressure (NG SUPPLY PRESS) 2. Oil tank temperature (OIL TANK TEMP) 3. Oil temperature after cooler (OIL TEMP AFT COOLER) 4. Turbine bearing temperature (TEMP TURB BRG) 5. Turbine speed 6. Generator bearing vibration (VIB GIN BRG CSG TE) 7. Burner temperature and other related oil and vibration parameters.
Ratio of faulty to normal data	No exact numerical percentage was specified, but it was noted that the manually collected data included missing and invalid values, which were cleaned during the preprocessing phase. This indicates the existence of faulty data, which was addressed to ensure data quality.
Data limits (thresholds)	Operational limits were clearly defined for each parameter, for example: • NG supply pressure: Normal (21.2–60), Warning (60.1–64.5), Fault (>64.5 or <21.2). • Oil tank temp: Normal (35–65), Warning (65.1–66), Fault (>66 or <35). • Turbine bearing temp: Normal (65–95), Warning (95.1–97), Fault (>97 or <65). • Turbine speed: Normal (>60), Fault (<60). • Vibration: Normal (9.3–13.7), Warning (13.71–14), Fault (>14 or <9.3).

2.3 Model Development and Training

The following deep learning algorithms were implemented:

- **Long Short-Term Memory (LSTM)** [16]**:** For capturing long-term dependencies in time-series data.
- **Gated Recurrent Units (GRU)** [17]**:** A computationally efficient alternative to LSTM.
- **Temporal Convolutional Networks (TCN)** [18]**:** For parallel processing of sequential data.

These algorithms are among the most effective tools for analyzing complex time series data, such as power plant data. These algorithms have a high ability to capture long-term patterns and gradual changes in data, enabling them to predict failures and detect anomalies with great accuracy. These technologies also allow for the processing of massive amounts of live data collected from sensors and help build proactive maintenance systems that reduce unplanned outages and lower operational costs. Table 4, shows a comparison between these algorithms.

Table 3: Normal Operating Ranges, Warning Limits, and Fault Thresholds for Key Sensor Readings in the Power Plant

Parameter	Normal Range	Warning Range	Fault Range
NG SUPPLY PRESS	21.2 – 60	60.1 – 64.5	>64.5 or <21.2
OIL TANK TEMP	35 – 65	65.1 – 66	>66 or <35
OIL TEMP AFT COOLER	35 – 70	70.1 – 72	>72 or <35
TEMP TURB BRG	65 – 95	95.1 – 97	>97 or <65
TEMP TURB BRG (duplicate)	65 – 95	95.1 – 97	>97 or <65
Turbine speed	>60	—	<60
VIB GIN BRG CSG TE	9.3 – 13.7	13.71 – 14	>14 or <9.3

Figure 1 illustrate the basic architecture of the GRU, LSTM, and TCN algorithms [13,14,15]

Figure 1 Basic architecture of GRU, LSTM, and TCN algorithms

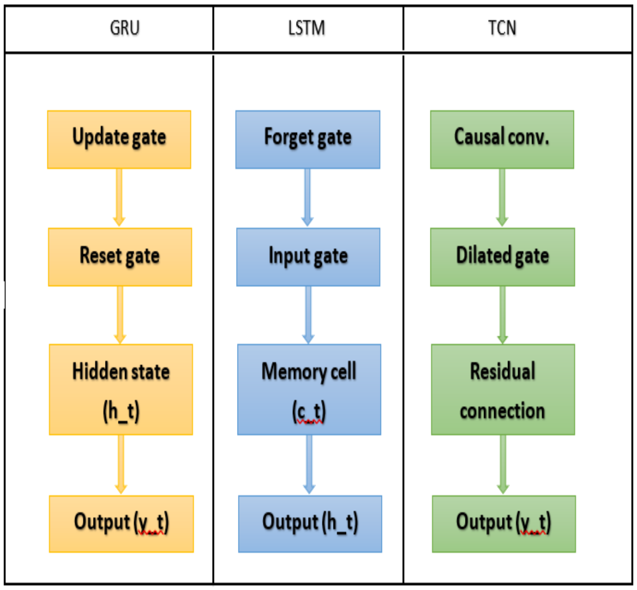

Fig. 1 Basic architecture of GRU, LSTM, and TCN algorithms

The LSTM, GRU, and TCN models were selected in this study for their strong ability to handle time-series data accurately and efficiently capture long-term patterns, while maintaining simpler architecture and faster training. In contrast, more complex models such as transformers and hybrid CNN-LSTM require larger datasets, higher computational resources, and are less practical for real industrial applications that demand fast and reliable solutions.

3. Results and Discussion

This section will present the accuracy and loss results for the training and validation processes of the three algorithms used in this study.

4.1 GRU Algorithm Performance evaluation

The GRU algorithm, as shown in Figure 2, demonstrates strong performance in analyzing power plant data, as evidenced by the trends in accuracy and loss over 50 training epochs. The model achieves a training accuracy of approximately 0.81 and a higher validation accuracy of 0.83, indicating effective generalization without overfitting. Meanwhile, the loss values decrease significantly, starting from 0.86 (training) and 0.65 (validation) and stabilizing at approximately 0.54 and 0.51, respectively. These results highlight the GRU model's ability to efficiently learn data patterns, enabling accurate predictions for proactive maintenance.

Table 4, shows a comparison between these algorithms

Algorithm	**Strengths**	**Limitations**	**Suitability for Power Plant Data**
LSTM	Captures long-term dependencies	Computationally intensive	High
GRU	Efficient, similar to LSTM	Slightly less memory capacity	High
TCN	Parallel processing, fast inference	Less interpretable	High
Algorithm	Strengths	Limitations	Suitability for Power Plant Data
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4.2 LSTM Algorithm Performance evaluation

As shown in Figure 3, the LSTM model achieves a stable training accuracy (~0.81) and a slightly higher validation accuracy (~0.83), which are good values indicating good generalization without overfitting. The training and validation losses decrease significantly during the initial stages before stabilizing at low levels, reflecting the effective ness of learning and error reduction. These results confirm the importance and reliability of LSTM in predicting potential failures, enabling cost-effective maintenance strategies and improving operational efficiency in power plants.

4.3 TCN Algorithm Performance evaluation

Figure 4 demonstrates the effectiveness of the TCN algorithm in predictive maintenance in power plants, with training accuracy reaching 81%, while validation accuracy consistently maintained at 83%. The loss curve shows a sharp drop from >3.0 to <0.6. These results demonstrate the TCN model's strong performance in predicting equipment behavior (accuracy ranging from 81% to 83%) and reducing errors (loss <0.6), which enhances maintenance decision-making and reduces unplanned outages.

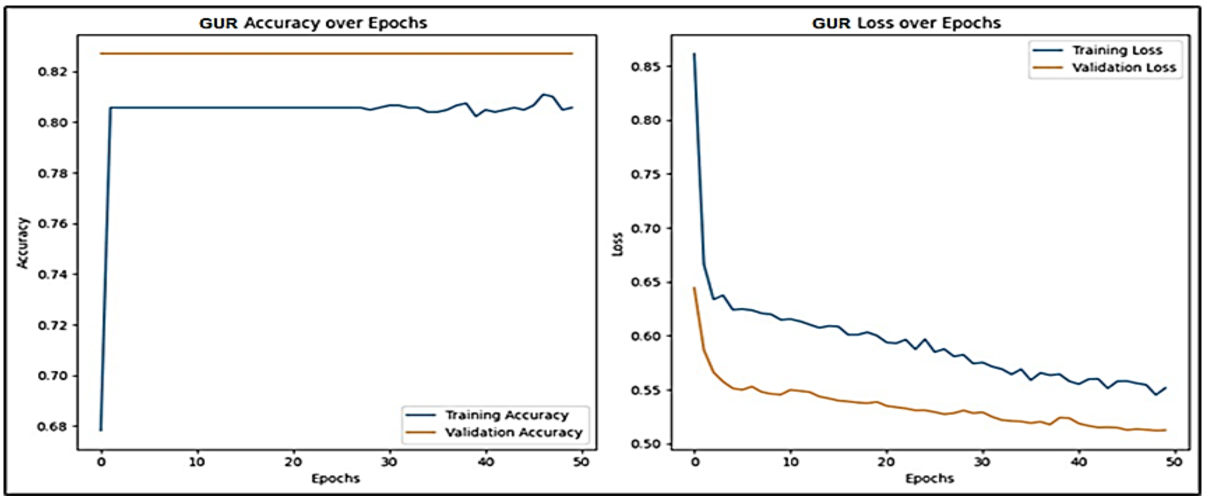

Fig. 2 Performance Evaluation of GRU Model

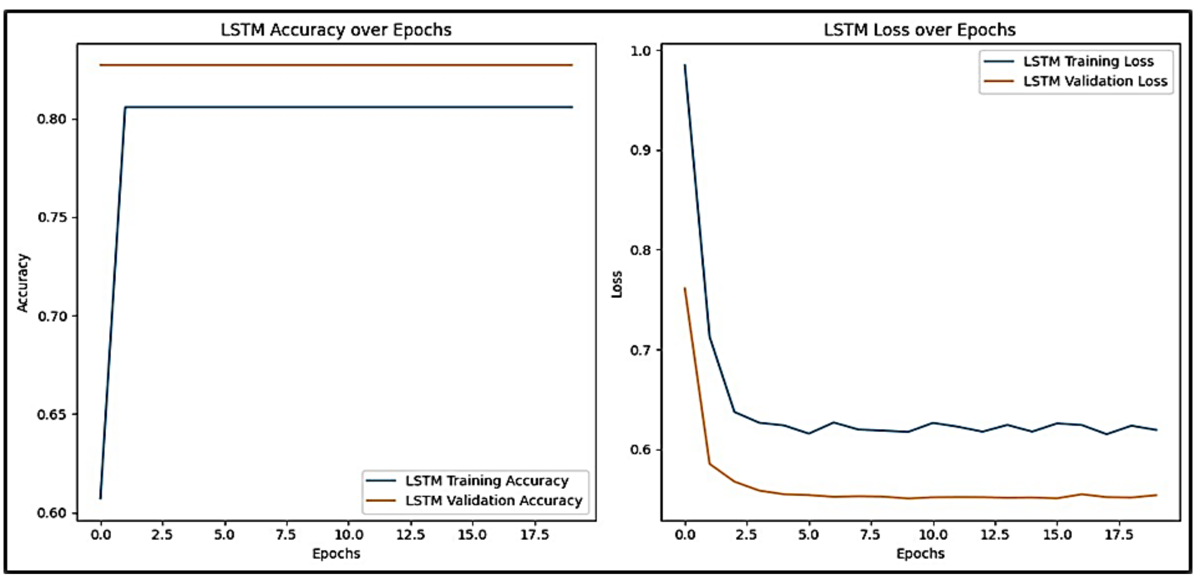

Fig. 3 Performance Evaluation of LSTM Model

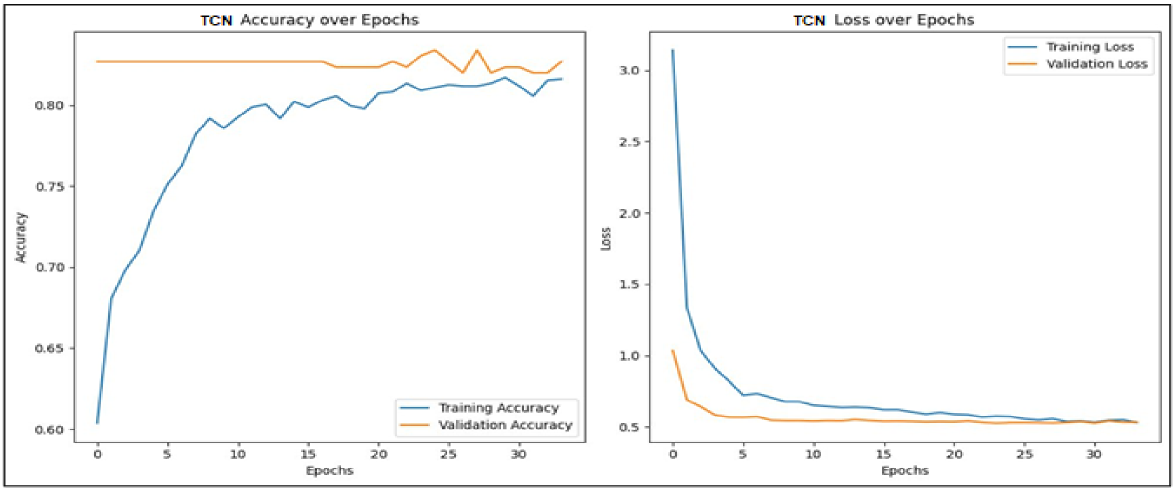

Fig. 4 Performance Evaluation of TCN Model

Conclusions

This study demonstrates the significant potential of AI-based predictive maintenance in power plants. Three deep learning models (GRU, LSTM, and TCN) were evaluated for power plant maintenance optimization, and all demonstrated excellent performance. The GRU algorithm, in particular, demonstrated a robust and effective solution for anomaly detection and maintenance optimization. GRU demonstrated stable convergence, with a validation accuracy of 0.82 and a loss decreasing to 0.50, demonstrating balanced training without overfitting. LSTM achieved a similar accuracy (0.80) but required more epochs (17.5 versus 50 for GRU) to stabilize, with slightly higher loss values than GRU. TCN exhibited more variable performance—while it reached a high training accuracy (0.80), its loss values span a wider range (0.5–6.0), and the model trained faster (30 epochs), indicating potential overfitting risks. Based on these results, GRU can be considered the most reliable option, offering the best balance between accuracy (0.82), loss reduction (down to 0.50), and training stability across all epochs. These results highlight GRU's superior potential for predictive maintenance applications in power plants, although LSTM remains a viable alternative but requires slightly longer training. TCN, on the other hand, may be suitable in scenarios that prioritize rapid deployment over maximum accuracy.

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