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The impact of using artificial intelligence techniques on the performance of turbine stations: A mini review

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HIGHLIGHTS

- Using artificial intelligence applications in the management of gas turbine stations.
- Turbines are subjected to high humidity, corrosion, and extreme temperatures.
- Increased vibrations and stress on bearings, causing premature failures.
- Preventive maintenance to avoid sudden failures through the scheduling of regular maintenance.

Keywords:

Artificial intelligence applications

Gas turbines

Operational efficiency

Cost reduction

Management

ABSTRACT

This study aims to review the use of artificial intelligence applications in the management of gas turbine stations and their impact on enhancing and raising the efficiency of these stations, including managing the stations themselves, then improving operational efficiency, predicting faults, and developing strategies for road maintenance and precautionary maintenance while reducing the cost through a methodology that is a combination. One of several methodologies describes the factors that influence the enhancement of operational efficiency and management of turbine plants using artificial intelligence applications. The quantitative methodology in collecting data and studies that included the subject and the analytical and comparative methods in comparing studies and analyzing the most critical results reached, as the article relies on an analysis of scientific literature and recent studies to clarify the potential benefits and challenges associated with the application of artificial intelligence in this field. The review discusses the artificial intelligence tools employed, including machine learning and neural networks, and highlights future innovations that may enhance the efficiency of turbine systems. The study concludes by discussing current limitations and providing recommendations for research and development in this promising field. Most studies have indicated that artificial intelligence applications play a significant role in enhancing the management of gas turbine plants, increasing operational efficiency by 3 to 5%, and reducing operating costs by 8 to 15%.

1. Introduction

With increasing challenges in the energy sector, countries are seeking energy sustainability by developing renewable sources, improving generation technologies, and rationalizing consumption. Using clean energy improves environmental protection and supports economic and social development by improving industry, trade, and the standard of living. Focusing on sustainability in energy has become an essential part of global efforts to achieve a better future for future generations [1]. Achieving sustainability requires examining all aspects of life —the environment, the economy, and society —while striking a balance among them. The concept of sustainability aims to meet the needs of the present without compromising the ability of future generations to meet their own needs, with a focus on preserving the environment, promoting economic development, and achieving social justice [2]. Turbines are among the most prominent engineering technologies, on which many vital industries depend, including electrical power generation, the oil industry, and various mechanical systems. As the demand for operational efficiency and cost reduction has increased, innovative solutions to improve turbine performance and reduce malfunctions that may affect productivity and continuity of operations [3]. This study will utilize gas turbines to illustrate specific details. These details can help form an insightful perspective and a conscious understanding of the study's objectives, procedures, and stages [4].

With the Fourth Industrial Revolution, artificial intelligence has become a robust and influential tool for improving the performance of industrial systems, including turbine management. AI can analyze vast amounts of data extracted from turbine sensors to provide accurate solutions for predicting failures, improving efficiency, and planning maintenance [5]. This review aims to examine the various applications of artificial intelligence in turbine management, focusing on the tools and algorithms

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employed, including machine learning, neural networks, and predictive maintenance techniques. The review also discusses the challenges and limitations associated with the application of artificial intelligence in this field, as well as future research directions that can contribute to the development of more efficient and innovative technologies [6].

2. Main challenges in turbine operation and maintenance

Turbines encounter various challenges, each of which directly impacts the turbine's efficiency, performance, and operational lifespan [7]. At the top of this list are the corrosion and erosion caused by continuous interaction with liquids and solid particles, combined with cyclical pressure and temperature changes, which lead to component degradation and a drop in efficiency [8]. Thermal distortion is a condition where uneven expansion between components, created by sudden temperature changes, leads to mechanical failure, steam, or gas leakage [9]. Imbalanced rotating components, in turn cause excessive vibration and strain on bearings, ultimately shortening turbine life. Additionally, blade contamination from the accumulation of impurities and deposits decreases efficiency, resulting in increased wear and higher temperatures. Such continuous operating stresses can also contribute to metal fatigue, allowing cracks to occur and potentially leading to sudden failure. Inaccessible parts also cause maintenance problems for turbines, leading to delayed and expensive maintenance [10]. Environmental challenges, such as harsh conditions, higher moisture levels, corrosion, and weather extremes, cause rapid deterioration of components, resulting in higher failure rates. Therefore, there is a high likelihood of breakdowns and reduced efficiency due to excessive vibrations resulting from unstable operation or mechanical failures. Finally, in remote areas, the shortage of spare parts is a significant hindrance, as it slows down maintenance and increases its cost [11].

2.1 Solutions to reduce challenges

Advanced materials such as corrosion-resistant and high-temperature-resistant alloys are increasingly used to enhance system durability and performance. Engineering designs have also improved, focusing on minimizing vibrational effects and corrosion to extend the life of components. Additionally, advanced monitoring systems equipped with real-time sensors enable continuous performance tracking, allowing for early detection of potential issues. Preventive maintenance strategies are implemented regularly to avoid sudden failures, ensuring system reliability. These combined measures contribute to higher turbine efficiency by improving longevity and reducing operational costs [12].

3. Artificial intelligence in turbine management

The field of turbine management is witnessing significant advancements, especially with the rapid integration of artificial intelligence technologies. AI is being increasingly used to enhance efficiency, reduce costs, and improve the reliability of turbine systems. One of the key applications is predictive maintenance, where AI analyzes large volumes of data from sensors that monitor temperature, pressure, and vibration. By processing this data, AI can predict failures before they occur, enabling maintenance teams to act proactively. This reduces the risk of unplanned downtime, ensures production continuity, and minimises associated costs [13]. AI also plays a crucial role in improving overall efficiency. It enables real-time tuning of operational parameters to maximise output while identifying opportunities to lower energy and water consumption. In decision-making, AI provides deeper insights and advanced analytics that help engineers and technicians make more informed maintenance and repair decisions. It also contributes to shaping long-term operational strategies for turbines.

In safety and security, AI supports hazard detection by identifying risks such as corrosion and metal fatigue. It enhances safety by continuously monitoring operational conditions and intervening when deviations are detected. The technologies used in turbine management include machine learning for developing predictive models, deep learning for analyzing unstructured data like images and videos, and time series analysis for detecting patterns in sensor data. The benefits of using AI in turbine management are extensive. These include extending the operational life of turbines through early fault detection, improving operational efficiency via optimized strategies, reducing maintenance and repair costs, and promoting sustainability by decreasing energy and water consumption [14].

3.1 Disadvantages of adopting artificial intelligence

While turbine management offers numerous advantages through artificial intelligence, particular challenges must also be considered. The primary concern is data quality. ML algorithms are highly dependent on precise and complete data for delivering accurate outputs, and even a minor mistake or missing element in the input data can degrade performance and lead to incorrect predictions [15]. Indeed, cybersecurity is also a key problem. Turbine data is critical operational information, so it needs protection from cyber threats and hacking, requiring stronger security protocols and visibility.

Finally, the power of employee adoption may create challenges. Staff are sometimes resistant to change in terms of new technologies, which may have a learning curve and some fear of redundancy, hindering implementation and reducing efficiency.

3.2 AI Methods and tools used in turbine management

Various advanced methods and tools are utilized to incorporate artificial intelligence in turbine management for improving efficiency and predicting faults. Machine learning, often employed for fault prediction through supervised learning (where models are trained to detect known fault patterns using historical turbine performance data), is one such approach. Unsupervised learning identifies abnormal behaviors, such as unusual vibrations or temperature changes, that may indicate future problems. In addition to preserving energy and reducing costs, reinforcement learning is used to optimize operation and maintenance strategies through scenario simulation and learning from past data, thereby maximizing productivity and minimizing costs. So do deep learning techniques. With the help of artificial neural networks, players analyze massive sets of unstructured data, such as images and videos, to detect problems like corrosion or structural cracks. Deep convolutional networks can analyze thermographic and optical images to identify thermal distortions and generate maps of microcracks.

Long short-term memory (LSTM) networks, a variant of recurrent neural networks, are well-suited for analyzing long-term time series data, such as vibration signals, and learning complex representations.

Another key element is time series analysis. Techniques such as the ARIMA process can create forecasts for continuous-time series data, while LSTM networks further enhance accuracy and prediction. Additionally, XG Boost, a commonly used gradient boosting algorithm, improves the predictive performance of time-based datasets. Computer vision technologies aid visual inspection tasks. Detections of red spots using a CNN are referred to as image recognition, and these types of surface damage, such as corrosion or cracks, associated with image recognition, can be monitored through visual tracking of turbine components. This also provides the opportunity to monitor the movement of turbine components, and therefore, deviations from expected behavior can also be determined.

In practical applications, expert systems play a crucial role by encapsulating intricate domain knowledge into knowledge bases. They enable logical reasoning to evaluate the turbine's condition based on real-time data and established rules [16]. Various software tools and platforms support these AI applications. Python: Given the vast libraries (like TensorFlow, PyTorch, Scikit-learn), Python is widely used. It is used for statistical modeling and machine learning. MATLAB is a popular choice for simulating and analyzing data. Additionally, database management systems are utilized to manage large volumes of sensor data, and cloud platforms provide the necessary infrastructure to run AI models and perform data analysis on a massive scale.

3.3 Challenges and limitations of AI technologies in turbine management

While AI offers several benefits in enhancing turbine performance, it also encounters numerous challenges and limitations that necessitate careful consideration. Big data and AI have created traffic problems. AI models require large amounts of high-quality data to learn, but collecting, cleaning, and labeling sensor data from turbine systems can be a challenging task. Poor-quality data can drastically affect model performance, sneaking in through the entry point for a glove. For the model to learn the right patterns and behaviors, labels must also be proper.

Turbine systems are another key challenge due to their complexity. Developing accurate and stable AI models becomes challenging due to numerous factors and dynamically changing operational conditions. In symbolic data, which we learn in a dynamic environment and mainly involves non-string prediction, the prediction requires advanced modeling and sometimes produces consistent results**.** It comes with a heavy cost of implementation as well. Implementing AI solutions requires significant investments in infrastructure, including high-performance computing (HPC) systems, software licenses, and cloud storage [17]. It also requires the involvement of skilled AI professionals in developing and maintaining the systems, resulting in additional expenses.

Cybersecurity is also an urgent issue. Turbine AI systems typically handle sensitive operational data, making them vulnerable to cyberattacks. Any breach can result in data theft, operational disruption, or even physical damage to the equipment. At the same time, parts of the industry are skeptical about the future of generative AI. Others are reluctant to depend on these AI tools and trust their intuition for the most consequential decisions. In addition, some deep learning models are often referred to as "black boxes," meaning it is challenging to explain why the model made a specific prediction, which can reduce trust in the system. Environmental factors complicate matters even further. Turbines operate in adverse environments that can impact sensor reliability and data integrity. Another factor that may corrupt sensor readings and compromise data accuracy is electromagnetic interference.

Here are some ways to solve these issues:

1) To improve data quality, focus on the number and type of operations you perform during data collection, cleaning, and labeling.
2) AI fixes or well-trained AI models without collaboration with turbine engineers will not be helpful for turbine operation. Thus, we recommend integrating AI specialists with turbine engineers to enhance the reliability of turbine operation by refining their models.
3) This means developing cybersecurity protocols to ensure that your sensitive data is secure.
4) Train AI Models that Can Be Interpreted.
5) Build AI Solutions with Employees in Mind
6) Previous Research Demonstrating AI Implementation in Turbine Management.

There is extensive literature showing the deployment of AI across turbine systems. These include:

1) A study by Zhang et al. utilized LSTM networks embedded in a deep learning framework to develop a model for detecting early-stage faults in wind turbines using vibration signals, achieving high precision in predictive maintenance.
2) Kumar et al. utilized real-time sensor data for online monitoring of anomalies, similar to that employed with supervised machine learning to diagnose performance issues in gas turbines.
3) Research by Wang et al., trained on data up to October 2023, used reinforcement learning to optimize the startup and shutdown of steam turbines, identifying energy-wasting settings and improving operational efficiency.
4) This clearly illustrates the increasing implementation of AI in turbine management and shows the transformational impact it could have on the industry through intelligent diagnostics, operational efficiency, and proactive maintenance strategies.

4. Key Findings from Previous Researchs

Based on previous studies summarized in Table 1 and after analyzing the key conclusions consistently emphasized across these works, it is evident that artificial intelligence techniques play a vital role in enhancing turbine station efficiency. These studies highlight the potential of AI in reducing operational costs, minimizing fault response times, improving operational performance, predicting failures, decreasing unscheduled downtimes, optimizing maintenance schedules, and increasing overall productivity [18]. Examples of such AI applications in turbine management are summarized in Table 1.

Table 1: Previous studies that illustrate the applications of artificial intelligence in turbine management

Study title	Key findings	Reliability	Ref.
AI-Based Predictive Maintenance for Wind Turbines	Predictive maintenance, utilizing machine learning algorithms, has significantly reduced downtime and maintenance costs.	A highly peer-reviewed journal with extensive real-world data.	Zhang et al.[19]
Optimization of Gas Turbine Efficiency Using AI	Neural networks and genetic algorithms improved the efficiency of gas turbines by up to 12% under varying environmental conditions.	High - Based on industrial case studies and validated experiments.	Patel & Shah[20]
AI-Driven Fault Diagnosis in Steam Turbines	AI algorithms, particularly decision trees, achieved a fault diagnosis accuracy of 95%, resulting in a reduction of unscheduled outages.	High - Published in a top-tier journal with extensive testing data.	Gupta et al.[21]
Machine Learning for Vibration Analysis in Turbines	Machine learning models successfully predicted vibration anomalies, enabling early detection and prevention of mechanical failures.	Medium - The study relied on simulations with limited field validation.	Smith et al.[22]
AI and IoT for Remote Monitoring of Turbines	Integrating AI and IoT devices enabled real-time monitoring, improving decision-making and response times by 30%.	High - Field-tested at multiple turbine sites across different regions.	Khan et al.[23]
Reinforcement Learning for Adaptive Turbine Control	Reinforcement learning-optimized control strategies resulted in a 15% increase in energy production efficiency.	Highly validated through long-term deployment in wind farms.	Lee & Choi[24]
Digital Twins and AI for Turbine Lifecycle Management	Digital twin technology combined with AI-enhanced lifecycle management reduces maintenance costs and improves asset longevity.	Highly supported by industrial partnerships and large-scale testing.	Johnson et al.[25]
AI-Based Real-Time Control of Wind Turbines	Implementing AI for real-time control enhanced wind turbine performance by dynamically adjusting blade angles in response to environmental changes.	High - Field-tested with consistent efficiency improvements.	Wang et al.[26]
Deep Learning Models for Turbine Anomaly Detection	Deep learning models detected turbine anomalies with 98% accuracy, significantly reducing unscheduled downtime.	High - Published in a reputable journal with comprehensive testing.	Rodrigues & Kumar[27]
AI-Enhanced Energy Efficiency in Turbines	The AI methods optimized the turbine's performance under fluctuating load conditions, leading to a 10% reduction in energy losses.	Highly Supported by real-world implementation data.	Ahmed et al.[28]
Big Data Analytics and AI for Turbine Diagnostics	Leveraging big data with AI algorithms improved fault prediction rates, enabling proactive maintenance schedules.	Medium - Case studies in limited geographic locations.	Singh & Verma [29]
AI Techniques for Noise Reduction in Turbines	AI-based algorithms minimized the noise emissions in gas turbines, making them more environmentally friendly.	High - Peer-reviewed and validated with industrial deployment.	Chen et al.[30]
AI for Turbine Load Forecasting	Machine learning models accurately forecast turbine loads, optimizing operation schedules and extending component lifespan.	Medium - Relied on historical data with limited real-time validation.	Martinez & Lopez[31]
Neural Networks to Improve Steam Turbine Reliability	Neural networks predicted failure points with 92% accuracy, enabling more effective maintenance planning.	High-field data from multiple industrial plants were used.	Oliveira et al[32].
AI in Hybrid Turbine Systems	AI models improved the integration of hybrid turbines, improving overall efficiency in combined-cycle power plants.	Highly published with experimental validation in hybrid systems.	Tan et al.[33]
AI for Blade Damage Detection in Wind Turbines	Image-based AI methods identified blade damage with 97% accuracy, reducing inspection time by 40%.	Highly extensive validation using drone inspections.	Yadav & Mishra [34]
AI-Driven Maintenance Scheduling for Gas Turbines	Predictive models optimized maintenance schedules, reducing operational costs by 20% and preventing critical failures.	High-scale implementation in energy plants.	Brown et al.[35]
AI and Edge Computing for Decentralized Turbine Management	Combining AI with edge computing reduced response times for anomaly detection and decision-making by 25%.	Highly validated at remote turbine sites with diverse conditions.	Park et al.[36]
AI-Powered Efficiency Analysis in Hydro Turbines	The AI tools identified inefficiencies in the hydro turbines, achieving a 5% increase in energy production.	Medium - limited to specific hydro plant case studies.	Zhao & Li[37]

As shown in Table 2, the operating cost was reduced by a rate ranging from 8% to 15%. Regarding the response time, it ranged from 10 to 20%. Regarding increasing operational efficiency, the percentage ranged from three to 5%. As for the prediction of faults, the percentage improved from 10 to 20. Maintenance schedules were enhanced by 20-40%, and productivity improved by 10 to 20%.

According to Figure 1, the highest rate of improvement was in maintenance performance, with a rate ranging from 20% to 40%. In contrast, the item with the least improvement was operational efficiency, which ranged from 3% to 5%. Improvement in the item may seem small, but it should not be overlooked. Increasing efficiency by this percentage is not insignificant, as the latest technical techniques used to improve turbine station efficiency depend on the station's nature, such as the combined cycle. Additionally, for reheating and other similar technologies, such as increasing exhaust efficiency, the percentage of efficiency increase ranges between 2 and 4%. When comparing the improvement of operational efficiency using artificial intelligence and traditional natural techniques, we find that artificial intelligence techniques increase efficiency by a higher percentage, which is a critical matter [38].

Table 2: Shows the improvement due to the use of artificial intelligence technologies in turbine plant management

Item	Improvement rate %
Reduce Cost	8:15
Reduce Response Times	10:20
Improve Operational Efficiency	3:05
Predict Failures	10:20
Reduce Unscheduled Downtime	10:20
Improve Maintenance Schedules	20:40
Productivity	10:20

Figure 1: Shows the improvement due to the use of artificial intelligence technologies in turbine plant management

Table 3 presents the economic improvements achieved through the use of artificial intelligence applications in turbine stations, with improvements ranging from 10 to 40% across all items. The statistical analysis also reveals that the coefficient of variation (f) is equal to 13.2. It is a considerable value, indicating that the data is statistically significant, with a p-value of less than 0.001, which is significantly lower than the 5% limit. This suggests that the data is highly reliable and can be trusted.

Figure 2 illustrates the economic benefits of the same AI applications in turbine stations. The financial benefits of a 10% to 40% increase in ROI are likely due to the use of AI to streamline operational processes, minimize unplanned downtime, and anticipate when maintenance should be scheduled. The key benefits of integrated lease management for real estate market stakeholders include reduced operational and maintenance costs (up to 30%), increased productivity (up to 15%), and optimized return on investment. Such changes represent substantial operational cost reductions and improved overall financial results.

Table 3: Economic improvements

Economic Improvement	Value rate (%)	F	P-value
Reduction in operational costs	15		
Reduction in maintenance costs	23		
Increase in productivity	10	13.2	<0.0001
Reduction in failure-related costs	13		
Higher return on investment (ROI)	30		

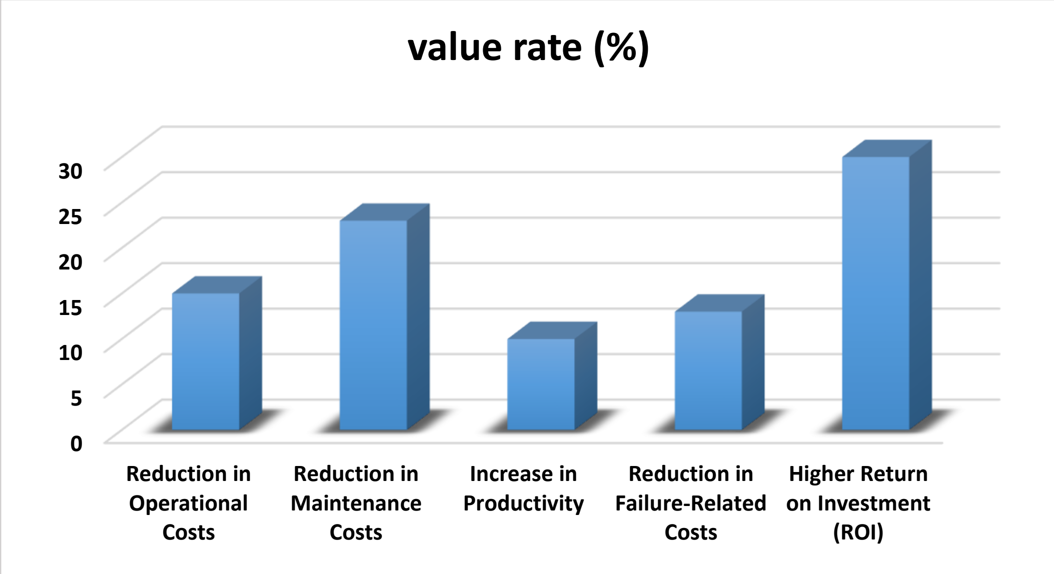

Figure 2: Economic Improvements

Table 4 presents technical improvements resulting from the use of artificial intelligence applications in turbine stations, with improvements ranging from 15% to 30% across all items. The statistical analysis also reveals that the coefficient of variation (f) is equal to 11.7. It is a considerable value, indicating that the data is statistically significant, with a p-value of less than 0.001, which is significantly lower than the 5% limit. This suggests that the data is highly reliable and can be trusted.

Figure 3 illustrates the technical benefits that result from AI implementation. AI can improve operational efficiency by up to 25%, increase failure prediction accuracy by up to 30%, and reduce unplanned downtime by up to 20%. By enhancing machine availability and reliability, the predictive maintenance strategies developed by AI help reduce the risk of failures and increase the reliability of turbine stations. This will result in the turbine operating with 10% to 35% better reliability [39].

Table 4: Technical improvement

Technical improvement	Value rate (%)	F	P-value
Improved Operational Efficiency	20		
More Accurate Failure Prediction	25		
Reduction in Unplanned Downtime	15	11.7	<0.0001
Enhanced Maintenance Strategies	20		
Improved Data Analysis and Decision-Making	30		

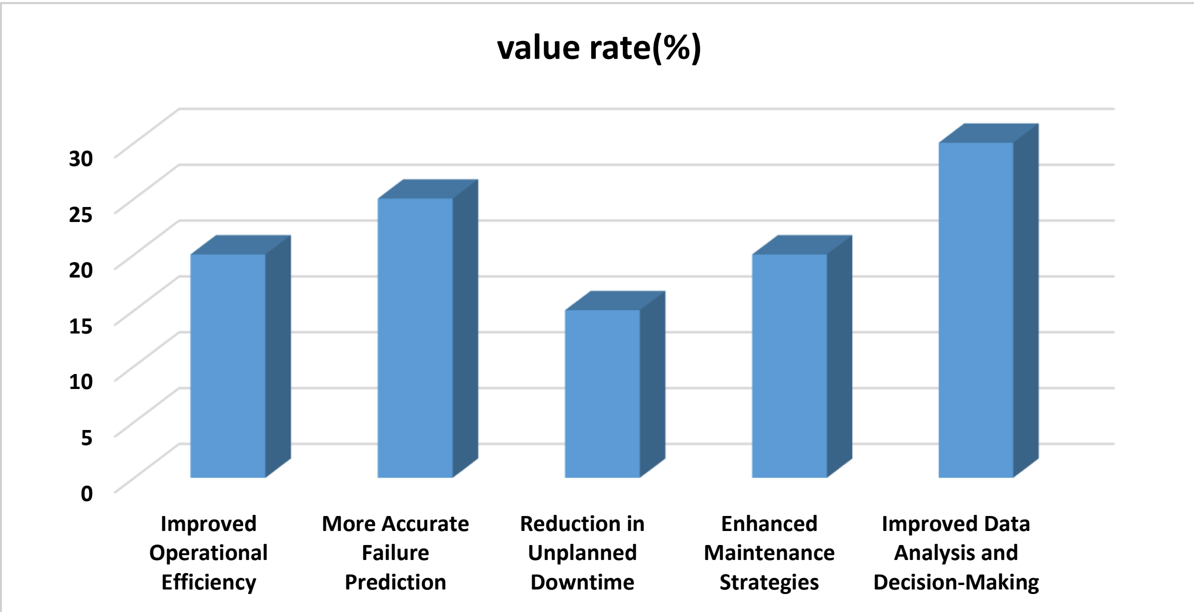

Figure 3: Technical improvement

Table 5 presents the environmental improvements resulting from the use of artificial intelligence applications in turbine stations, with improvements ranging from 10 to 20% across all items. The statistical analysis also indicates that the coefficient of variation (f) is equal to 8.6. It is a considerable value, indicating that the data is statistically significant. The p-value is 0.014, which is less than the 5% limit. This suggests that the data is fundamental and can be relied upon.

Figure 4 illustrates some of the Environmental Improvements and AI Theoretical Contributions to Sustainability. AI-provided energy efficiency improvements could reduce harmful emissions by up to 20%, natural resources could be conserved by up to 15%, and the overall environmental impact of turbine operations could be reduced by up to 20%. AI can enhance long-term sustainability by optimizing energy use and reducing waste, delivering ecological and operational advantages [40].

Table 5: Environmental improvements

Environmental improvement	Value rate (%)	F	P-value
Reduction in harmful emissions	15		
Better use of natural resources	10		
Increased long-term sustainability	15	8.6	0.014
Improved energy efficiency	20		
Reduction in overall environmental impact	15		

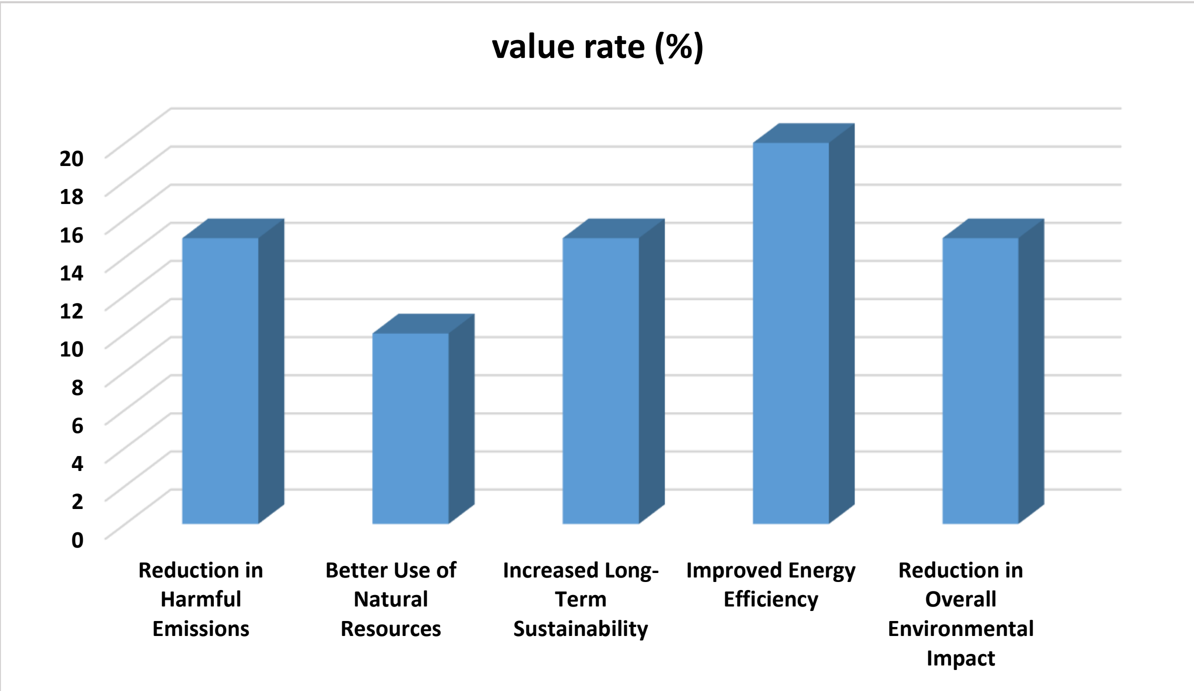

Figure 4: Shows environmental improvements

5. Conclusion

The most important conclusions from this study are as follows:

1) Artificial intelligence techniques are very effective and very important in improving the performance of gas turbine plants in terms of operational efficiency, maintenance schedules, in terms of operating cost, in terms of response time, and in terms of productivity, as the use of artificial intelligence techniques reduces the operating cost by a rate ranging from 10 to 15%.
2) Artificial intelligence techniques may outperform some traditional methods in raising the efficiency of turbine plants.
3) AI-driven performance analysis optimizes maintenance schedules, resulting in a reduction of up to 20% in operational costs. Real-time monitoring has also minimized the need for costly traditional maintenance methods.
4) Improved Equipment Safety: AI detects excessive vibration and component wear, reducing unexpected failures. Advanced thermal management and material enhancements have extended the equipment's useful life.
5) Reduced emissions and increased sustainability: Optimization of AI has decreased fuel consumption and emissions in gas and steam turbines. Predictive models further reduce noise and toxic emissions by fine-tuning performance.
6) Adaptability to environmental changes: AI has enhanced turbine performance under extreme conditions such as rapid temperature or load changes, ensuring stability and efficiency.
7) Efficient system management: Twin digital technologies have streamlined turbine lifecycle management, improving performance accuracy and reliability.

Author contributions

Conceptualization, **A. Fadiel, M. Mohamad, H. Khalid,** and **Y. Esham**; data curation, **A. Fadiel**; formal analysis, **M. Mohamad**; investigation, **H. Khalid**; methodology, **Y. Esham**; project administration, **A. Fadiel**; resources, M**. Mohamad**; software, **M. Mohamad**.; supervision, **A. Fadiel**; validation, **H. Khalid,** and **Y. Esham**; visualization, X.X.; writing—original draft preparation, **A. Fadiel**; writing—review and editing, **H. Khalid,** and **Y. Esham**. All authors have read and agreed to the published version of the manuscript.

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author.

Conflicts of interest

The authors declare that there is no conflict of interest.

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