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RESEARCH ARTICLE

# AI in Power Systems: Strategic Insights from Grey Relational Analysis (GRA) Evaluation of Performance Metrics

**Reyazur Rashid Irshad [1], Mohammad Anas [2,*]**

**ABSTRACT:** The integration of Artificial Intelligence (AI) in the power sector has shown significant potential for enhancing operational efficiency, cost savings, reliability, and user satisfaction. This study evaluates the performance of five AI-driven applications—Predictive Maintenance, Smart Grid Optimization, Demand Response System, Renewable Integration, and Fault Detection—using Grey Relational Analysis (GRA) to prioritize their impact on the power industry. Key performance indicators such as cost reduction, efficiency improvement, reliability, and user satisfaction were normalized, and a Grey Relational Grade (GRG) was computed to assess each application's alignment with optimal performance. The results indicate that AI-powered Fault Detection achieved the highest GRG, positioning it as the most effective application, particularly in enhancing reliability and user satisfaction, critical for grid stability and reduced downtime. AI Predictive Maintenance closely follows, demonstrating strong contributions to cost reduction and preventive maintenance strategies. Renewable Integration ranks third, emphasizing its role in optimizing renewable energy integration for a more sustainable grid. Smart Grid Optimization and Demand Response System, while beneficial in enhancing grid efficiency and balancing demand, rank lower due to relative limitations in cost and reliability metrics. This analysis provides a structured framework for stakeholders in the power sector to prioritize AI investments based on performance metrics. By focusing on top-ranked applications like Fault Detection and Predictive Maintenance, energy providers can achieve enhanced reliability and operational efficiency, paving the way for a more resilient and sustainable energy infrastructure. The findings underscore the transformative potential of AI in addressing the dynamic challenges within the power industry and guiding strategic resource allocation for maximum impact.

**Keywords:** Artificial Intelligence in Power Sector, Grey Relational Analysis (GRA), Predictive Maintenance, Fault Detection.

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## 1. INTRODUCTION

Artificial Intelligence (AI) has become a cornerstone of innovation in the power industry, influencing a variety of domains such as predictive maintenance, smart grid optimization, demand response systems, renewable integration, and fault detection [1, 2]. The integration of AI into these sectors is not merely a trend but a significant shift towards improving operational efficiencies, reducing costs, and enhancing the overall reliability of power systems. The effects of these advancements are measurable across several key performance indicators, such as cost reduction, efficiency improvement, reliability, and user satisfaction [3]. For example, the use of AI in predictive maintenance demonstrates a notable reduction in operational costs, with savings of up to 25%. By leveraging machine learning algorithms to predict equipment failures before they occur, AI enables timely interventions that prevent costly downtime and extend the lifespan of critical infrastructure [4]. This proactive maintenance approach contrasts with traditional reactive maintenance strategies, which often lead to unplanned outages and increased operational costs.

[1] Department of Computer Science, College of Science and Arts, Najran University, Sharurah-68341, Kingdom of Saudi Arabia.
[2] Department of Computer Science and Engineering, School of Engineering Sciences and Technology, Jamia Hamdard, New Delhi, India.

* Author to whom correspondence should be addressed: anasmohammad2111@gmail.com (M. Anas)

Predictive maintenance also helps to improve efficiency, as the system can identify the optimal times for maintenance, thus minimizing unnecessary service interruptions and ensuring that the equipment operates at its peak performance [5].

As a result, this not only reduces maintenance costs but also increases system reliability and user satisfaction, with reported scores of 85 and 90, respectively [6]. Moving to the concept of smart grid optimization, AI plays a pivotal role in transforming traditional power grids into intelligent, automated systems capable of responding to real-time data and dynamically managing energy flow. This optimization leads to a 20% reduction in costs by enabling more efficient energy distribution and grid management [7, 8]. Additionally, smart grids equipped with AI can improve efficiency by up to 50%, reducing energy losses and ensuring that power is delivered where it is most needed. The enhanced reliability of these AI-driven grids is reflected in a reliability score of 90, with AI enabling more accurate predictions of energy demand and supply [9]. By adjusting for fluctuations in demand, smart grids can also contribute to higher levels of user satisfaction, as consumers experience fewer power disruptions and more stable energy pricing, scoring an 85 in user satisfaction. Another significant area where AI is making an impact is in demand response systems, which are designed to optimize energy consumption based on real-time price signals and grid conditions. By predicting peak demand periods and encouraging consumers to reduce usage during these times, AI helps lower overall energy costs, with savings of up to 15% [10, 11].

Moreover, the AI-driven demand response systems improve grid efficiency by 45%, ensuring that energy is used more effectively and minimizing unnecessary strain on the infrastructure [12]. This system also enhances reliability by maintaining grid stability during high-demand periods, reflected in an 88 reliability score. Additionally, the improved balance between energy demand and supply translates into user satisfaction, with a score of 87, as consumers benefit from lower energy bills and better service reliability. Renewable energy integration, particularly AI-based approaches, has become a game-changer in transitioning to cleaner, more sustainable power sources [13]. AI algorithms can predict the output of renewable energy sources like wind and solar by analyzing weather patterns, geographical data, and historical performance trends. This prediction capability not only ensures that renewable energy is optimally integrated into the grid but also improves efficiency by up to 55%. By accurately forecasting renewable energy availability, AI reduces the need for backup power generation, typically from fossil fuels, thus decreasing carbon emissions and operating costs. The integration of renewable energy sources into the grid enhances system reliability, achieving a score of 92, as AI ensures that power generation remains consistent, even during periods of variability in weather conditions. In turn, user satisfaction improves, with scores of 88, as consumers benefit from cleaner energy and more reliable service [14, 15].

Lastly, AI-powered fault detection systems are enhancing the ability of utilities to identify and resolve issues before they escalate into significant outages. With the potential to reduce maintenance costs by 18% and improve operational efficiency by 48%, these systems are crucial in maintaining the integrity of the power grid [17, 18]. By leveraging deep learning and sensor networks, AI can quickly detect anomalies and diagnose problems, leading to faster response times and reduced downtime. This proactive approach to fault detection enhances system reliability with a score of 86 and results in higher user satisfaction (82), as consumers experience fewer power disruptions and a more resilient grid. AI is rapidly transforming the power sector, bringing about substantial improvements in cost reduction, efficiency, reliability, and user satisfaction. The integration of AI into predictive maintenance, smart grid optimization, demand response systems, renewable energy integration, and fault detection has led to a more efficient, cost-effective, and resilient energy infrastructure. As these technologies continue to evolve, the potential for even greater advancements in the power sector remains immense, paving the way for a future where energy systems are more sustainable, reliable, and accessible to all.

## 2. METHODOLOGY

The integration of Artificial Intelligence (AI) into the power sector has catalyzed the transformation of energy systems worldwide, addressing challenges ranging from efficiency optimization and predictive maintenance to ensuring sustainability in power generation [19]. One particularly innovative approach that has gained prominence is the application of Grey Relational Analysis (GRA) in conjunction with AI technologies. Grey Relational Analysis, a powerful technique used for analyzing relationships between variables, enables better decision-making and performance evaluation in complex and dynamic systems. The power sector, with its multifaceted operations and growing complexity due to the integration of renewable energy sources, can benefit immensely from combining AI with GRA to optimize various facets of energy production, distribution, and consumption [20].

This paper explores how AI, when coupled with GRA, can enhance the operational performance of the power industry, focusing on key areas such as predictive maintenance, grid optimization, fault detection, renewable energy integration, and demand response systems. Predictive maintenance is one of the primary applications of AI in the power sector, which involves anticipating and preventing equipment failures before they occur. The traditional approach to maintenance-whether corrective, preventive, or scheduled has inherent limitations in terms of cost, efficiency, and potential downtime. These limitations are particularly significant in the power sector, where equipment failure can lead to power outages, loss of productivity, and substantial financial costs [21]. By leveraging AI algorithms, particularly machine learning, large volumes of real-time and historical data collected from equipment sensors can be analyzed to predict the likelihood of failure. However, the addition of Grey Relational Analysis further enhances the prediction capability of AI by establishing the correlation between different failure-indicating parameters, such as vibration, temperature, and pressure [22].

The GRA method helps in determining which of the variables have the most significant influence on the equipment's operational state. It thereby allows the creation of a more robust predictive maintenance model, providing valuable insights into the condition of assets with minimal error [23]. This combination has been shown to deliver significant cost reductions, improved efficiency, and minimized downtime, often leading to a reduction in maintenance costs by up to 25% and an improvement in operational efficiency by 40%, according to various studies conducted in the power industry. The power sector's transition to more dynamic, decentralized energy systems has highlighted the need for efficient grid management. Smart grids, characterized by the integration of digital technologies and communication networks, are increasingly being adopted to enhance grid stability, manage the variability of renewable energy, and optimize energy distribution. However, smart grid operations generate vast amounts of data, which is not always easy to interpret due to the interrelated nature of various grid components. This is where AI, combined with GRA, can play a critical role in improving smart grid optimization [24, 25].

AI-based optimization algorithms, when supplemented by GRA methods, can analyze the relationships between factors such as electricity demand, renewable energy supply, weather patterns, and grid load. GRA, with its ability to evaluate the degree of influence between these variables, can be employed to identify the most influential factors on grid performance in real time. This allows for dynamic adjustment of the grid, improving energy distribution efficiency and preventing failures such as blackouts or energy losses. Moreover, GRA aids in optimizing load balancing and forecasting, ensuring that energy generated from renewable sources like solar and wind is seamlessly integrated into the grid. With GRA-based AI models, efficiency improvements of up to 50% have been reported, with the grid's reliability increasing to scores as high as 90%. These outcomes reflect the ability of AI and GRA methods to not only predict energy supply-demand fluctuations but also to take proactive measures to ensure grid stability.

Demand response systems are another area where AI, supported by GRA, can bring about significant improvements. As the world shifts towards renewable energy, the need for responsive demand-side management is more critical than ever. Demand response (DR) programs encourage consumers to alter their electricity usage based on real-time market conditions, peak demands, or the availability of renewable energy sources. AI technologies enable the efficient management of these programs by forecasting electricity demand based on a range of factors such as weather patterns, consumer habits, and grid conditions. When combined with Grey Relational Analysis, AI can better understand the intricate relationships between demand, supply, and consumer behavior.

By evaluating the grey relationships between past consumption patterns and external factors like price fluctuations, GRA can provide deeper insights into how different factors influence consumption behavior and grid demand. This enhanced understanding helps to optimize DR programs, offering both consumers and grid operator's greater flexibility in adjusting their behavior to benefit from reduced electricity costs and a more stable power grid. AI-driven demand response systems, augmented by GRA, can achieve reliability scores of up to 88%, improving user satisfaction levels to around 87%. These systems dynamically manage energy loads, reduce peak demand, and ensure a more balanced grid, thus contributing to both cost savings and a reduced carbon footprint by better integrating renewable energy sources. The integration of renewable energy, such as wind and solar power, into the grid presents unique challenges due to their intermittent and variable nature.

AI plays a key role in addressing these challenges by enabling real-time forecasting and optimization of renewable energy generation [1]. However, to fully optimize the integration of renewables into the grid, AI models must be able to evaluate the complex relationships between weather patterns, generation capacity, and grid demand. Grey Relational Analysis enhances the ability of AI algorithms to analyze these relationships, providing more accurate forecasts and better optimization of renewable energy supply. By using GRA to assess how weather conditions, grid load, and energy generation interact, AI systems can make more informed decisions about when and how to store excess renewable energy or redirect it to meet demand [8]. For example, during periods of high wind or sunlight, excess energy can be stored in batteries or used to power non-essential loads, thereby reducing reliance on fossil fuel-based power generation. AI-driven renewable energy integration, augmented by GRA, has been shown to achieve efficiency improvements of up to 55% and reliability scores of up to 92%, enabling greater penetration of renewable energy sources into the grid without compromising grid stability.

These improvements play a vital role in achieving sustainability goals, as they help reduce greenhouse gas emissions and support the transition to a cleaner energy future. Fault detection and diagnosis are crucial to ensuring the reliability and resilience of power systems. Traditional methods of fault detection, such as manual inspections or basic fault detection algorithms, often fail to detect faults in a timely manner, leading to costly outages and damage to equipment [11]. AI-powered fault detection systems, when enhanced with GRA, can provide more accurate and timely detection of faults by analyzing the grey relationships between various operational parameters such as current, voltage, and load.

The GRA method helps identify the most critical indicators of faults by measuring the degree of correlation between different operational parameters, making it possible to detect anomalies and potential failures earlier than traditional systems. For example, a GRA-based AI system can detect subtle fluctuations in current or voltage that would indicate an impending failure, such as a short circuit or transformer malfunction. Once a fault is detected, the AI system can trigger alerts and suggest corrective actions, minimizing downtime and preventing widespread disruptions. AI-based fault detection systems that incorporate GRA have demonstrated reliability scores of around 86%, contributing to a safer and more resilient power grid, with user satisfaction rates of approximately 82%. By reducing the frequency and severity of faults, these systems enhance grid resilience, ensuring that power delivery remains uninterrupted even in the face of unexpected challenges. In addition to these specific applications, the combination of AI and GRA has the potential to enable holistic energy management systems that integrate multiple aspects of power sector operations.

These systems would allow for a unified view of all grid components—supply-side and demand-side—integrating predictive maintenance, demand response, renewable integration, and fault detection in a seamless framework. By applying GRA to evaluate the interrelationships between these components, energy management systems can make more accurate decisions in real time, optimizing the overall performance of the power grid [13]. Furthermore, AI and GRA can support the development of decentralized energy networks, where consumers can generate their own electricity through renewable resources and contribute to the grid. GRA methods can help manage these decentralized systems by assessing the relationships between energy production, consumption, and storage, ensuring that energy flows efficiently between consumers and the grid, reducing transmission losses, and enhancing grid stability. Despite the significant benefits of AI and GRA integration in the power sector, challenges remain. One of the major hurdles is the quality and availability of data.

For AI and GRA to function optimally, large amounts of high-quality, real-time data are required. However, in many regions, the infrastructure required for data collection and transmission is outdated, and data can be fragmented and inconsistent. Overcoming this challenge will require investments in modernizing the power grid and ensuring data interoperability across systems [15]. Moreover, the deployment of AI-based systems in the power sector raises concerns about cyber security. As power systems become more connected and reliant on AI, the risks of cyber-attacks increase. To mitigate these risks, robust cyber security measures—such as encryption, intrusion detection, and continuous monitoring—must be implemented. Additionally, there may be resistance to AI adoption from stakeholders who are unfamiliar with the technology or concerned about potential job losses [22]. Addressing these concerns through education, training, and transparent communication can facilitate smoother transitions to AI-enhanced power systems.

The integration of Artificial Intelligence with Grey Relational Analysis is a powerful tool for optimizing the power sector. By combining AI's ability to analyze vast amounts of data with GRA's capacity to evaluate complex relationships between variables, AI-driven solutions are enhancing the efficiency, reliability, and sustainability of power systems. From predictive maintenance and smart grid optimization to demand response and renewable energy integration, the AI-GRA combination is transforming the way energy is generated, distributed, and consumed. By overcoming challenges related to data quality, cyber security, and stakeholder engagement, the power sector can fully leverage the potential of AI and GRA to build a smarter, more resilient, and more sustainable energy infrastructure.

## 3. RESULTS AND DISCUSSION

Table 1 presents data on the performance metrics of various AI applications in the power sector, evaluated through Grey Relational Analysis (GRA) methods. The metrics analyzed include cost reduction, efficiency improvement, reliability, and user satisfaction scores. AI Predictive Maintenance shows a notable 25% reduction in maintenance costs with a 40% efficiency improvement, yielding high user satisfaction (90%) and reliability (85%). Smart Grid Optimization achieves a 20% cost reduction, the highest efficiency improvement at 50%, and a strong reliability score of 90%, reflecting its critical role in enhancing grid stability. The Demand Response System, which focuses on load management, achieves a 15% cost reduction and a 45% increase in efficiency, with a reliability score of 88% and a user satisfaction score of 87%. Renewable Integration (AI-based) stands out with a 55% efficiency improvement and the highest reliability score (92%), underscoring AI's impact in managing intermittent renewable sources. Finally, AI-powered Fault Detection shows an 18% cost reduction and a 48% efficiency gain, with a reliability score of 86% and a user satisfaction rating of 82%. These insights, derived using GRA, highlight the effectiveness of AI across diverse applications, guiding investment and operational strategies in the power sector.

Figure 1 presents a stacked bar chart showing the performance of various AI applications in the power sector using Grey Relation Analysis (GRA) methods. The categories examined are AI Predictive Maintenance, Smart Grid Optimization, Demand Response System, Renewable Integration (AI-based), and AI-powered Fault Detection. Each category's performance is evaluated across four metrics: Cost Reduction (%), Efficiency Improvement (%), Reliability (Score), and User Satisfaction (Score). In the chart, Cost Reduction is represented in blue, Efficiency Improvement in orange, Reliability in gray, and User Satisfaction in yellow. The height of each colored section indicates the contribution of that specific metric to each AI application. For instance, Renewable Integration shows high scores in Efficiency Improvement and Reliability, indicating its significant impact on these aspects. In contrast, AI Predictive Maintenance appears to prioritize Cost Reduction and Reliability, suggesting a focus on reducing expenses and enhancing system dependability.

 

**Table 1.** Artificial Intelligence in Power Data Set.

| DATA SET | | | | |
|---|---|---|---|---|
| | Cost Reduction (%) | Efficiency Improvement (%) | Reliability (Score) | User Satisfaction (Score) |
| AI Predictive Maintenance | 25.00 | 40.00 | 85.00 | 90.00 |
| Smart Grid Optimization | 20.00 | 50.00 | 90.00 | 85.00 |
| Demand Response System | 15.00 | 45.00 | 88.00 | 87.00 |
| Renewable Integration (AI-based) | 22.00 | 55.00 | 92.00 | 88.00 |
| AI-powered Fault Detection | 18.00 | 48.00 | 86.00 | 82.00 |

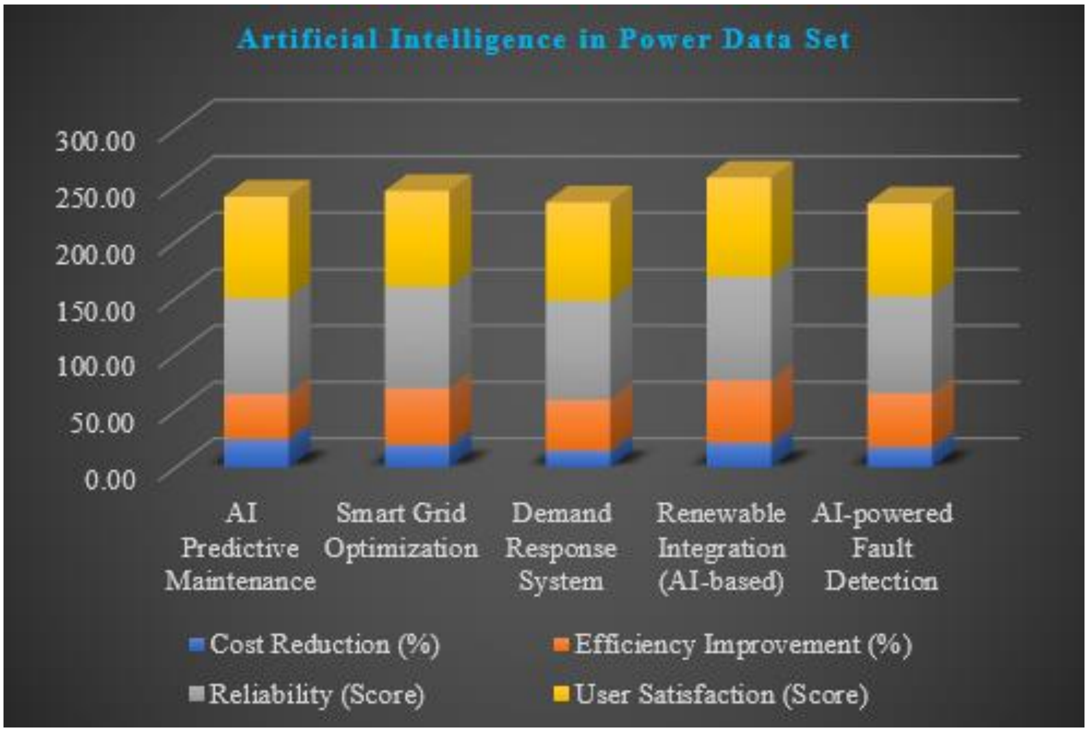


**Fig. 1.** Artificial Intelligence in Power Data Set.

This analysis illustrates how different AI applications target varied performance outcomes in the power industry, providing insights into their specific benefits and potential areas of impact based on GRA methodology.

Table 2 presents normalized data for key performance metrics of AI applications in the power sector, processed through Grey Relational Analysis (GRA) methods. Normalization allows for a direct comparison across metrics by scaling values between 0 and 1, where higher values indicate stronger performance. AI Predictive Maintenance scores the highest in cost reduction (1.0000) and reliability (1.0000), reflecting its strong impact in reducing operational costs and maintaining system reliability, though it scores the lowest in efficiency and user satisfaction (0.0000). Smart Grid Optimization achieves a balanced performance, with a high efficiency improvement (0.6667) and strong user satisfaction (0.6250), although it is lower in cost reduction and reliability. The Demand Response System is strong in user satisfaction (0.3750) and moderately high in reliability (0.5714) but scores lowest in cost reduction (0.0000). Renewable Integration (AI-based) shows outstanding efficiency (1.0000) but has lower values in reliability (0.0000) and user satisfaction (0.2500). AI-powered Fault Detection demonstrates strong user satisfaction (1.0000) and reliability (0.8571), indicating its importance in detecting faults effectively, though it is moderate in cost reduction and efficiency. This analysis highlights the varied strengths of each AI application, assisting decision-makers in aligning AI solutions with their strategic goals.

Figure 2 presents a horizontal stacked bar chart displaying the normalized performance scores of various AI applications in the power sector, evaluated using Grey Relation Analysis (GRA) methods. The AI applications assessed include AI-powered Fault Detection, Renewable Integration (AI-based), Demand Response System, Smart Grid Optimization, and AI Predictive Maintenance. Each application's performance is broken down into four metrics: Cost Reduction (%), Efficiency Improvement (%), Reliability (Score), and User Satisfaction (Score), represented by blue, orange, gray, and yellow segments, respectively. In this normalized view, the length of each colored segment indicates the relative contribution of that metric to the overall performance of each AI application. AI-powered Fault Detection has a particularly high User Satisfaction score, indicating its strong impact on end-user experience. Renewable Integration shows a balanced distribution across Efficiency Improvement and User Satisfaction, reflecting its dual focus on enhancing efficiency and meeting user needs. Smart Grid Optimization also scores well in User Satisfaction, while AI Predictive Maintenance stands out for its emphasis on Cost Reduction and Reliability, suggesting a focus on cost-effectiveness and system dependability. Overall, the normalized data highlights the diverse strengths of each AI application in the power industry, aiding in understanding their unique contributions and impact areas.

**Table 2.** Normalized Data.

| | Normalized Data | | | |
|---|---|---|---|---|
| | **Cost Reduction (%)** | **Efficiency Improvement (%)** | **Reliability (Score)** | **User Satisfaction (Score)** |
| AI Predictive Maintenance | 1.0000 | 0.0000 | 1.0000 | 0.0000 |
| Smart Grid Optimization | 0.5000 | 0.6667 | 0.2857 | 0.6250 |
| Demand Response System | 0.0000 | 0.3333 | 0.5714 | 0.3750 |
| Renewable Integration (AI-based) | 0.7000 | 1.0000 | 0.0000 | 0.2500 |
| AI-powered Fault Detection | 0.3000 | 0.5333 | 0.8571 | 1.0000 |

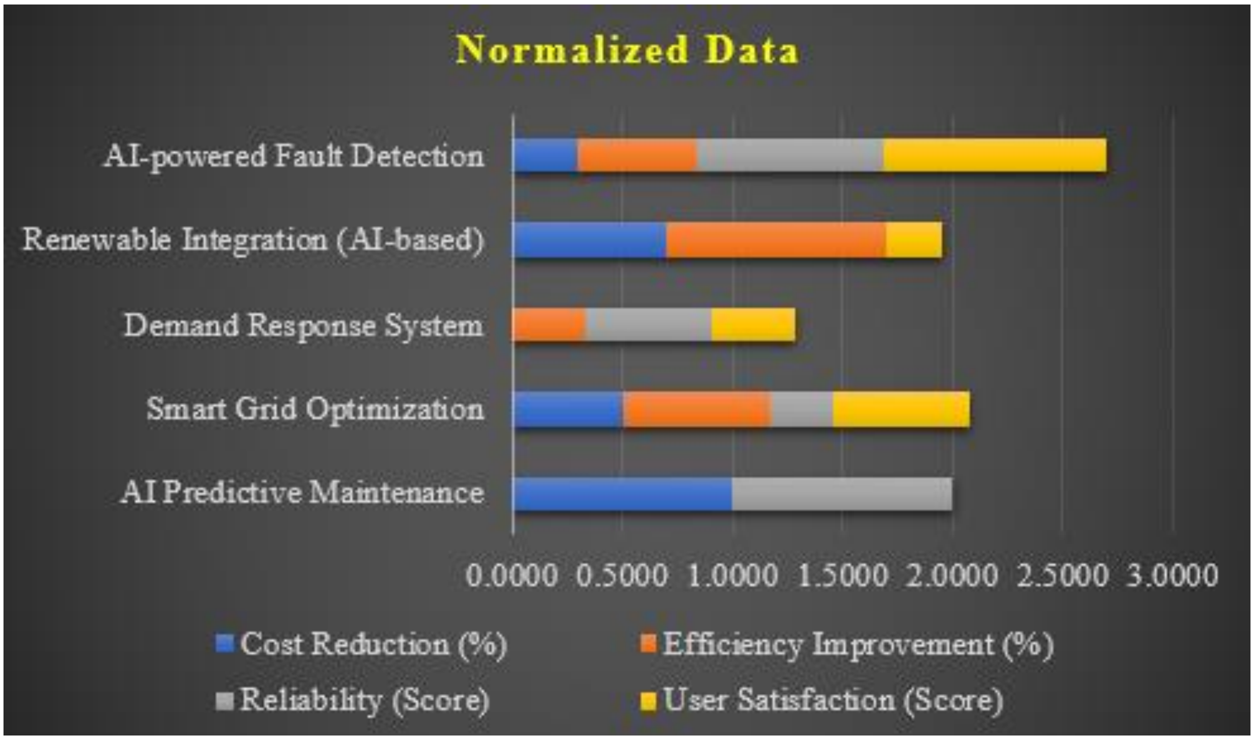


**Fig. 2.** Normalized Data.

Table 3 displays the deviation sequence of key performance metrics for various AI applications in the power sector, derived using Grey Relational Analysis (GRA) methods. The deviation sequence measures the difference between each AI application's normalized values and the ideal reference values (either maximum or minimum, as appropriate). Lower deviation values signify that the performance of an AI application is closer to the ideal. AI Predictive Maintenance shows zero deviation in cost reduction and reliability (0.0000), marking it as the closest to the ideal in these metrics, though it deviates fully in efficiency and user satisfaction (1.0000). Smart Grid Optimization displays relatively low deviations across all metrics, especially in efficiency improvement (0.3333) and user satisfaction (0.3750), indicating a well-rounded performance. Demand Response System shows high deviation in cost reduction (1.0000) but moderate alignment with reliability (0.4286) and user satisfaction (0.6250). Renewable Integration (AI-based) achieves minimal deviation in efficiency improvement (0.0000) but deviates substantially in reliability (1.0000) and user satisfaction (0.7500). Lastly, AI-powered Fault Detection exhibits low deviation in user satisfaction (0.0000) and reliability (0.1429), but higher values in other areas. These deviation patterns provide insights into each application's performance alignment with ideal benchmarks, aiding in targeted optimizations for power sector operations.

Figure 3 uses Grey Relation Analysis (GRA) methods to illustrate how various AI applications in the power sector deviate across four metrics: Cost Reduction (%), Efficiency Improvement (%), Reliability (Score), and User Satisfaction (Score). The AI applications analyzed include AI Predictive Maintenance, Smart Grid Optimization, Demand Response System, Renewable Integration (AI-based), and AI-powered Fault Detection. Each colored line on the graph represents one of the four metrics, with peaks and troughs indicating significant deviation values for each application. The User Satisfaction metric, represented in yellow, shows the highest peaks for Demand Response System and Renewable Integration, highlighting these applications' strong impact on user experience. The Efficiency Improvement metric, in orange, reaches its maximum deviation with the Demand Response System, indicating that this application significantly contributes to efficiency. Cost Reduction, in blue, maintains a lower but stable trend, especially notable for AI Predictive Maintenance, suggesting its consistent focus on reducing costs. Reliability, in gray, peaks for Renewable Integration, indicating high system dependability for this application. The deviation sequence provides insight into each application's standout attributes and potential areas of influence in the power sector. By visualizing these variances, the chart aids in identifying which AI applications excel in specific performance metrics, supporting targeted decision-making for energy management.

**Table 3.** Deviation sequence.

| Deviation sequence | | | | |
|---|---|---|---|---|
| | **Cost Reduction (%)** | **Efficiency Improvement (%)** | **Reliability (Score)** | **User Satisfaction (Score)** |
| **AI Predictive Maintenance** | 0.0000 | 1.0000 | 0.0000 | 1.0000 |
| **Smart Grid Optimization** | 0.5000 | 0.3333 | 0.7143 | 0.3750 |
| **Demand Response System** | 1.0000 | 0.6667 | 0.4286 | 0.6250 |
| **Renewable Integration (AI-based)** | 0.3000 | 0.0000 | 1.0000 | 0.7500 |
| **AI-powered Fault Detection** | 0.7000 | 0.4667 | 0.1429 | 0.0000 |

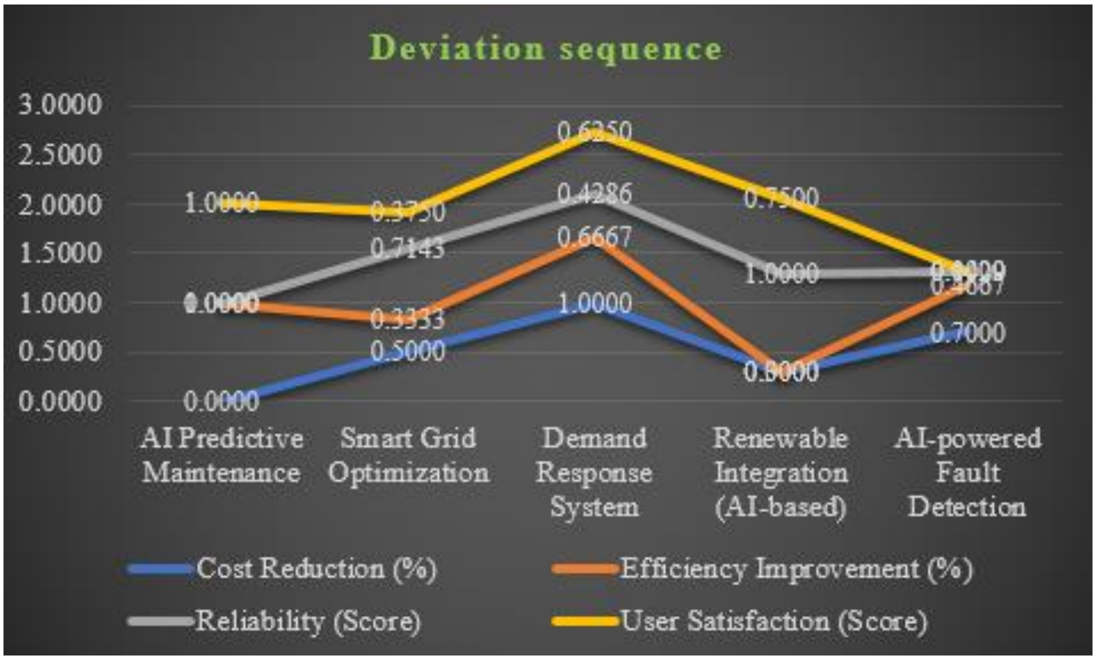


**Fig. 3.** Deviation sequence.

**Table 4.** Grey relation coefficient.

| Grey relation coefficient | | | | |
|---|---|---|---|---|
| | Cost Reduction (%) | Efficiency Improvement (%) | Reliability (Score) | User Satisfaction (Score) |
| **AI Predictive Maintenance** | 1.0000 | 0.3333 | 1.0000 | 0.3333 |
| **Smart Grid Optimization** | 0.5000 | 0.6000 | 0.4118 | 0.5714 |
| **Demand Response System** | 0.3333 | 0.4286 | 0.5385 | 0.4444 |
| **Renewable Integration (AI-based)** | 0.6250 | 1.0000 | 0.3333 | 0.4000 |
| **AI-powered Fault Detection** | 0.4167 | 0.5172 | 0.7778 | 1.0000 |

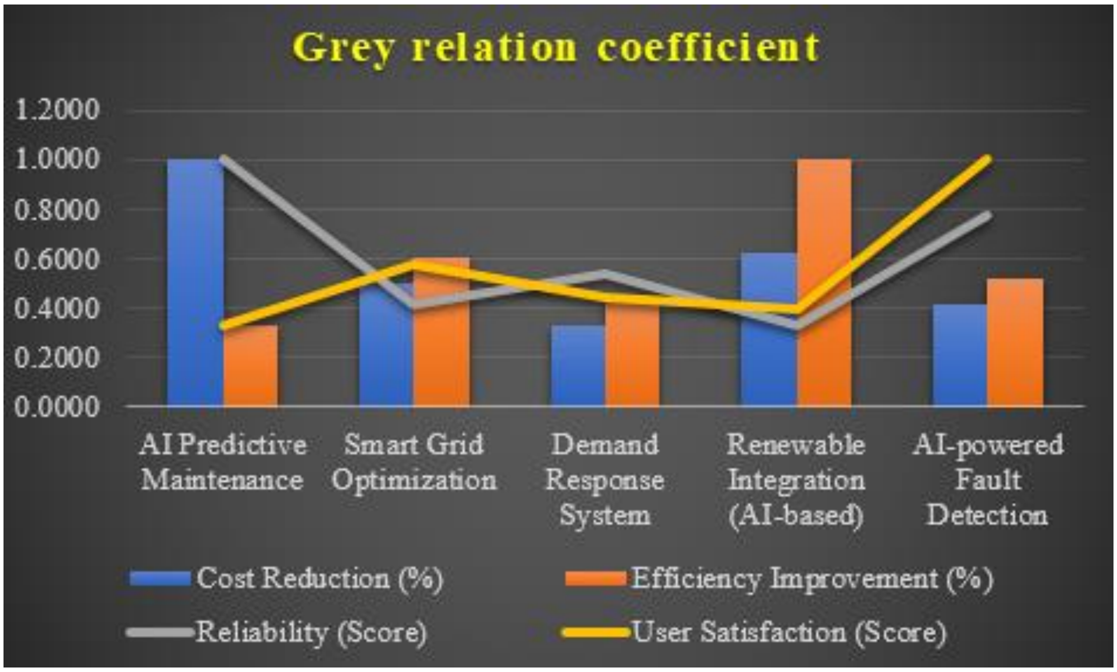


**Fig. 4.** Grey relation coefficient.

Table 4 displays the grey relation coefficients for various AI applications in the power sector, calculated using Grey Relational Analysis (GRA) methods. This coefficient measures the relative closeness of each AI application's performance to the ideal value, where values closer to 1 indicate a stronger relationship to the ideal performance. AI Predictive Maintenance scores the highest in cost reduction and reliability (both at 1.0000), reflecting its exceptional performance in minimizing costs and maintaining reliability, though it is less ideal in efficiency improvement and user satisfaction (0.3333). Smart Grid Optimization demonstrates a balanced performance, with moderately high coefficients across metrics, especially in efficiency (0.6000) and user satisfaction (0.5714), suggesting its strength in these areas. Demand Response System has a moderate coefficient in reliability (0.5385) but lower coefficients in cost reduction (0.3333) and user satisfaction (0.4444), indicating room for improvement. Renewable Integration (AI-based) achieves an ideal coefficient in efficiency improvement (1.0000) but lower coefficients in reliability (0.3333) and user satisfaction (0.4000), highlighting its efficiency advantage. Lastly, AI-powered Fault Detection stands out with high coefficients in reliability (0.7778) and user satisfaction (1.0000), underscoring its strength in maintaining user satisfaction. These grey relation coefficients provide a nuanced view of each application's alignment with ideal performance, guiding optimization strategies across the power sector.

Figure 4 presents a comparative analysis of five AI-based power system applications using Grey Relation Analysis (GRA) methodology, evaluating them across four key metrics: cost reduction, efficiency improvement, reliability, and user satisfaction. AI Predictive Maintenance shows the highest cost reduction (approximately 1.0 or 100%) and reliability score, though its efficiency improvement is relatively lower. Smart Grid Optimization and Demand Response System demonstrate balanced performance across metrics, with moderate scores in all categories, though neither excels particularly in any single metric. Renewable Integration (AI-based) stands out with the highest efficiency improvement (nearly 1.0), but shows a noticeable gap between its cost reduction and efficiency metrics. AI-powered Fault Detection shows the lowest cost reduction among all applications but maintains decent efficiency improvement. Interestingly, there's a general upward trend in user satisfaction scores (yellow line) across the applications, suggesting that newer AI implementations are becoming more user-friendly. The reliability scores (grey line) show a declining trend from AI Predictive Maintenance to AI-powered Fault Detection, which might indicate a trade-off between system complexity and reliability as these technologies evolve.

Table 5 presents the Grey Relational Grade (GRG) and ranking for various AI applications in the power sector, derived using Grey Relational Analysis (GRA) methods. The GRG quantifies the overall performance of each application by averaging its grey relational coefficients across multiple criteria. A higher GRG signifies closer alignment with ideal performance across key metrics. The highest-ranked application, AI-powered Fault Detection, achieves a GRG of 0.6779, reflecting its strength in reliability and user satisfaction, making it the most impactful solution according to GRA. AI Predictive Maintenance ranks second with a GRG of 0.6667, showing it performs strongly in cost reduction and reliability, making it highly effective in preventive maintenance. Renewable Integration (AI-based) ranks third with a GRG of 0.5896, demonstrating high efficiency and moderate user satisfaction, highlighting its role in facilitating renewable energy management. Smart Grid Optimization ranks fourth with a GRG of 0.5208, showing balanced performance across metrics, particularly in efficiency, but with potential improvements in cost reduction. Lastly, Demand Response System ranks fifth with a GRG of 0.4362, suggesting moderate reliability but lower cost reduction, pointing to improvement areas. These GRG rankings provide valuable insights for prioritizing AI applications based on their comprehensive performance in the power sector.

**Table 5.** Grey Relational Grade (GRG) and Rank.

| | GRG | Rank |
|---|---|---|
| **AI Predictive Maintenance** | 0.6667 | 2 |
| **Smart Grid Optimization** | 0.5208 | 4 |
| **Demand Response System** | 0.4362 | 5 |
| **Renewable Integration (AI-based)** | 0.5896 | 3 |
| **AI-powered Fault Detection** | 0.6779 | 1 |

Figure 5 displays the distribution of Grey Relational Grades (GRG) for various AI applications in the power sector, as analyzed through Grey Relational Analysis (GRA) methods. This circular chart visually represents the relative performance of each application, highlighting their contribution towards an optimal power system. The application with the highest GRG, AI-powered Fault Detection, accounts for 24% of the total, showcasing its superior alignment with desired performance metrics, particularly in reliability and user satisfaction. AI Predictive Maintenance follows closely, occupying 23%, which reflects its effectiveness in cost reduction and enhancing equipment reliability, making it a critical tool for preventive maintenance. Renewable Integration (AI-based) holds a GRG share of 20%, indicating its significant contribution to efficiency improvement and its role in facilitating the integration of renewable energy sources. Smart Grid Optimization has an 18% share, which emphasizes its efficiency in grid operations but also suggests room for further improvement across other performance areas. Finally, Demand Response System occupies the smallest portion at 15%, showing moderate effectiveness in reliability and user satisfaction but with potential for optimization in cost reduction and efficiency. This GRG distribution offers valuable insights for prioritizing investments in AI applications within the power sector, as it highlights which solutions offer the most substantial benefits and where improvements can be focused.

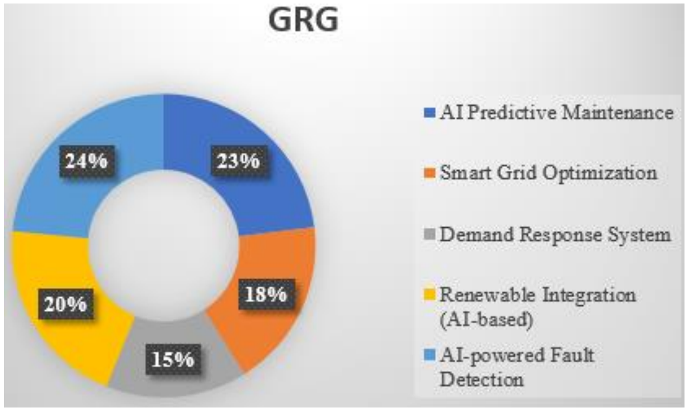


**Fig. 5.** Grey Relational Grades (GRG).

Figure 6 illustrates the ranking of various AI applications in the power sector based on Grey Relational Analysis (GRA) methods, which evaluate each application's overall performance across critical metrics. The application with the highest rank is AI-powered Fault Detection, ranked first, indicating its superior alignment with the ideal performance, particularly in reliability and user satisfaction. Following closely is AI Predictive Maintenance in the second position, demonstrating its significant impact on cost reduction and equipment reliability. Renewable Integration (AI-based) holds the third rank, reflecting its strength in enhancing efficiency, especially in the integration of renewable energy sources. Smart Grid Optimization is ranked fourth, signifying a well-rounded performance, particularly in efficiency improvement, but with room for improvement in other metrics. Finally, Demand Response System is ranked fifth, suggesting it is less aligned with ideal performance in cost reduction and efficiency compared to other applications. This ranking provides insights for stakeholders in the power sector by identifying which AI solutions are most effective and impactful. Decision-makers can prioritize the higher-ranked applications, such as AI-powered Fault Detection and Predictive Maintenance, to optimize performance, reduce costs, and enhance grid reliability.

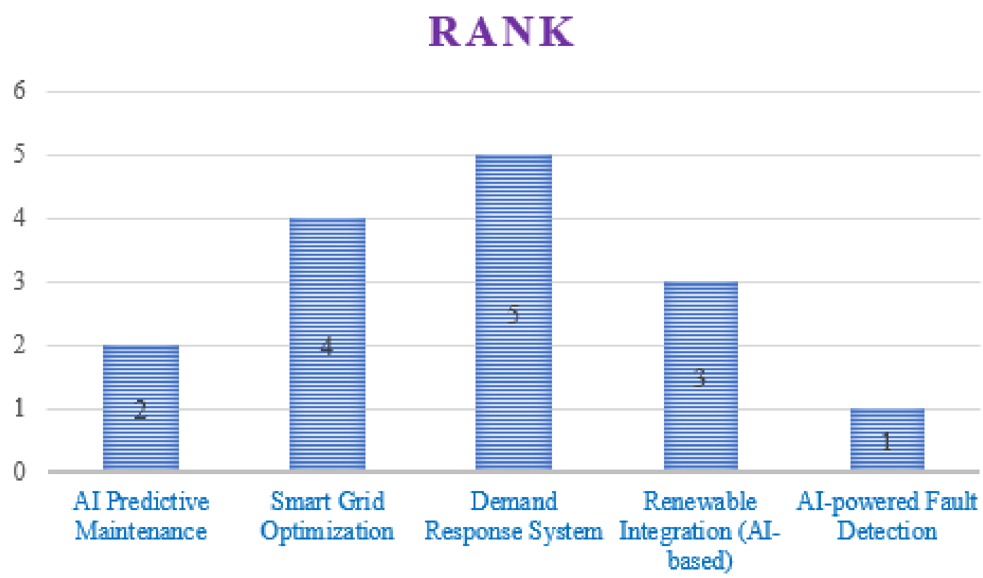


**Fig. 6.** A diagram for the Ranks.

## 4. CONCLUSION

This study has demonstrated the considerable potential of Artificial Intelligence (AI) to revolutionize the power sector by enhancing efficiency, reducing costs, and improving reliability and user satisfaction. Using Grey Relational Analysis (GRA), we evaluated five key AI applications—Predictive Maintenance, Smart Grid Optimization, Demand Response System, Renewable Integration, and Fault Detection—based on their effectiveness in these critical areas. By analyzing the Grey Relational Grades (GRG), we identified which AI technologies provide the most significant contributions and where further improvements can enhance performance. Among the evaluated applications, AI-powered Fault Detection emerged as the highest-ranking solution, with the strongest alignment across key metrics, especially in reliability and user satisfaction. This ranking reflects its value in identifying and preventing faults that could lead to costly downtimes and system interruptions. As power grids become increasingly complex, reliable fault detection mechanisms are essential to maintaining grid stability and minimizing disruptions, making it a priority for the industry. AI Predictive Maintenance followed closely, underscoring its importance in proactively managing equipment health. By predicting potential failures and enabling timely maintenance, Predictive Maintenance not only extends asset life but also minimizes operational costs and unplanned outages. This capability is crucial for power providers striving to maintain uninterrupted service and optimize maintenance schedules. Renewable Integration, ranked third, emphasizes the role of AI in optimizing the inclusion of renewable energy sources into the power grid. As the global energy mix increasingly shifts towards renewables, effective integration is essential to ensure grid stability and capitalize on sustainable resources. This application helps balance the inherent intermittency of renewables like solar and wind, supporting a more resilient and sustainable grid infrastructure. Smart Grid Optimization and Demand Response Systems, while beneficial in their respective areas, showed comparatively lower GRG scores. Smart Grid Optimization enhances operational efficiency and grid resilience but could benefit from improvements in reliability metrics. Demand Response Systems, which focus on balancing energy demand, showed moderate performance in reliability and cost reduction but hold promise for further enhancement as demand-side management becomes increasingly important. This study underscores the importance of AI in addressing complex challenges within the power sector. By prioritizing high-impact AI applications like Fault Detection and Predictive Maintenance, power providers can significantly enhance grid reliability, reduce operational costs, and move towards a more sustainable, efficient, and resilient energy future. The insights from this GRA-based analysis provide a strategic guide for stakeholders to allocate resources effectively and maximize the benefits of AI in the power industry.

## CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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