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RESEARCH ARTICLE

Integrating IoT and AI for Advanced Predictive Maintenance: Innovations in Condition Monitoring Systems using MOORA method

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ABSTRACT: Moreover, as organizations implement robust predictive maintenance strategies, they can leverage artificial intelligence (AI) to minimize human intervention in data analysis, leading to more automated and self-sustaining maintenance systems. This progress has been demonstrated by using machine learning methods such as critical decision trees and neural networks to analyze operational data and predict equipment failure. The validation of machine learning models against actual operational data enhances the reliability of these predictive maintenance systems, providing a strong foundation for their broader application. The development of condition monitoring systems for industrial equipment is driven by advances in data transmission, storage technologies, and decreasing costs of reliable sensors. Also, Internet of Things (IoT) enables instant exchange of detailed data collected from various monitoring devices. This partnership creates a valuable opportunity for predictive maintenance by integrating efficient data collection with advanced analytics. For example, image-based predictive maintenance using drone camera surveys for structural monitoring is gaining popularity in various industries. The results indicate that Model E achieved the highest rank, while Model D had the lowest rank being attained. The value of the dataset Using AI for Predictive Maintenance, according to the MOORA method, Model E achieves the highest ranking.

Keywords: MOORA Method, Condition Monitoring Systems, Internet of Things (IoT), Predictive Maintenance

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1. INTRODUCTION

In recent years, advances in data transmission and storage technologies, combined with lower costs and increased sensor reliability, have accelerated the development of condition monitoring systems for industrial equipment. Whereas the Internet of Things (IoT) facilitates real-time exchange of detailed data collected from a range of monitoring devices. This advance provides a significant opportunity to improve condition monitoring data for predictive maintenance by integrating effective data collection with thorough analysis [1]. Image-based predictive maintenance is rapidly being adopted in various fields. For example, drone camera surveys are increasingly used for structural monitoring. Similar to applications in renewable energy and health care, it aims to perform routine inspections to detect potential problems in buildings, bridges, and construction sites or telecommunications infrastructure. In these fields, advances in image classification driven by deep learning algorithms are moving towards frequent and routine predictive maintenance [2]. Once a comprehensive, robust and mature predictive maintenance strategy is implemented, more business opportunities arise, allowing high-value assets to generate additional revenue rather than simply incurring costs. Predictive maintenance is in line with the future of AI, where operations are maintained autonomously without the need for human intervention. In this context, AI will take predictive maintenance a step further by eliminating the need for manual analysis of samples and outputs, surpassing current approaches that still require some level of human supervision [3].

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The aim is to implement a proof-of-concept approach in a controlled environment to evaluate the feasibility of using AI-driven machine learning as a fundamental component in a Predictive Maintenance System (ESPs) for Electric Submersible Pumps. To achieve this, data from the SCADA Historian database was used, containing a similar timeline of ESP operations, including normal operation and failure events, as input to a machine learning neural network [4]. We designed and simulated the operation of several predictive maintenance systems using this dataset. In our research, we evaluated the performance of three model classes: two decision-tree-based methods, Cree and random forests, as well as a third technique, logistic regression. Logistic regression was used as the basis for comparison because regression techniques are standard for data analysis, logistic regression being the usual choice when the dependent variable is discrete [5]. We have extended this framework to include neural network-based models that provide a more comprehensive description. These descriptive models were developed using artificially generated training data obtained from spatial block bootstrapping, as obtaining labeled training data for body component wear is expensive and time-consuming. Finally, we will explain how this interpretable AI framework can be used in other predictive maintenance and health monitoring applications [6].

Maintenance, prevention, and repair of critical aircraft components, including engines, hydraulic systems, and actuators, depend on a routine maintenance schedule. To remain competitive in today's aerospace market, it is critical to develop innovative maintenance solutions to ensure maximum aircraft service life and safety [7]. The research questions guided a systematic mapping process, assisting other researchers in analyzing trends, identifying key research directions, and drawing valuable insights and perspectives in the field [8]. The infrastructure was initially established by connecting machines through sensors and gateways, resulting in an Internet of Things (IoT) platform. This facilitated reliable access to data from production lines and integrated computer systems, forming the basis for building a predictive maintenance system [9]. Described as "condition-based maintenance conducted following the prediction, ongoing analysis or assessment of recognized characteristics and critical parameters associated with material degradation". The key concept of this approach is to analyze historical data to identify equipment behavior patterns and predict potential failures. After identifying these failure modes and predicting their timing, maintenance tasks can be planned in advance [10-12].

Our aim is to outline the most recent techniques in published research related to predictive maintenance using machine learning (ML) or deep learning (DL) methods. This research provides a comprehensive literature review that lays a strong foundation for machine learning (ML) and deep learning (DL) methods, highlighting their performance and results [13]. AI methods are adept at uncovering hidden data patterns and can effectively handle complex features, making them highly promising for accurate predictions. However, they demand significant computational resources, and their performance may vary depending on the hyper parameter settings chosen [14]. Recent studies have improved maintenance practices by exploring programming methods, classifying vehicle conditions, and using artificial intelligence algorithms to predict mechanical breakdowns. This method considers a number of weighted factors that can affect vehicle maintenance [15, 16]. By integrating these technologies in innovative ways, we have been able to save mere cost and time in maintenance. Instead, they used them to facilitate condition monitoring (CM) and condition-based maintenance (CBM), allowing operators to maintain more efficiently and intelligently. In other words, they developed and implemented a highly proactive and predictive maintenance model enhanced by AI and ML. This approach can reduce costs and reduce production disruptions by preventing equipment breakdowns [17-20].

2. MATERIALS AND METHODS

MOORA is a multi-criteria decision-making approach that has significant potential to comprehensively evaluate alternatives in the face of considerable heterogeneity and multiple influencing factors. The MOORA method is a multi-objective optimization approach designed to effectively address complex decision-making problems. The objective is to find the optimal alternative, considering a range of often conflicting criteria. In essence, it evaluates both favorable and unfavorable criteria simultaneously [23].

This paper presents a ratio structure approach using the MOORA method, where performance ratings of alternatives are represented as interval-valued triangular fuzzy numbers. The proposed extension includes a group decision-making framework that enables decision-makers to contribute their individual input. Performance evaluations can be conducted using exact values, intervals, or triangular fuzzy numbers. Individual performance ratings collected using this method is then transformed into group performance ratings, which are represented as interval-valued triangular fuzzy numbers [24].

The process of determining criterion weights using Analytical Hierarchy Process (AHP) involves inputs from multiple experts or group decision making for each topic. The MOORA method is used for ranking because it uses straightforward analytical ratios, has little mathematical complexity, and eliminates the need for complex calculations or advanced math skills. Additionally, it promotes two or more conflicting objectives criteria while keeping the computation time low [25]. In real-time manufacturing, the decision-making process becomes more complex due to the varying interests and values of various decision-makers. Effective decision-making requires a clear, systematic and logical approach to solving relevant problems. This method considers both beneficial (enhancing) and ineffective (decreasing) alternatives to create the most appropriate alternatives and eliminate alternatives that are unsuitable for reinforcement [4]. The proposed port planning uses the MOORA method, which includes two components, i.e. rate system and reference point. As this research is only concerned with simulating port planning, we determined the types and importance of objectives and alternatives separately. Key stakeholders include national and local authorities and contributing agencies. In this regard, consumer sovereignty applies only implicitly to the productive sector [6].

This study proposes a hybrid approach that combines the MOORA method with target programming, which evaluates qualitative and quantitative criteria to identify the best loan applicant firm and set optimal loan limits across firms [8]. The MOORA method uses both ratio structure and reference point approaches. Subsequent developments introduced a fully multiplicative form, resulting in a robust technique for multimodal, multi-objective optimization. Both MOORA and MULTIMOORA methods have been used in many studies to deal with complex decision-making challenges [9]. Although the optimal choice for the non-traditional manufacturing process identified by MOORA methods has a significantly high positive constant correlation coefficient, the user can select the second option for production. Method if it is considered unreliable due to some constraints. Ultimately, the final decision should be a practical consideration, ensuring that all possible obstacles the user may encounter are addressed [11]. However, high values of AT and TW present challenges for analyzing fleet management. The gap between the MOORA method and the reference point approach seems larger than the difference between the MOORA and multi-MOORA methods [12]. In this context, ANP-MOORA methods are recommended to assess supply chain challenges to find optimal alternatives among various options. The ANP-based framework successfully integrates various multi-criteria decision-making (MCTM) methods into decision-making processes to improve the selection of an optimal supply chain [13]. The MULTIMOORA method improves on the MOORA method by combining ratio structure, reference point, and absolute multiplicative form. Each criterion is assigned a weight based on its importance as assessed by the decision maker. A pair wise comparison matrix generated by the AHP method is used to establish these weights, and finally, the laptop alternatives are ranked using the MULTIMOORA and MOOSRA methods [15].

3. RESULTS AND DISSCUSSION

Table 1 exhibits the data set using AI for predictive maintenance. Model E stands out with the highest cost savings of $25,000 and the lowest failure rate at 2%, indicating that it offers substantial financial benefits while maintaining reliability. However, its uptime of 91% is slightly lower than that of Model A (94%) and Model C (92%). Model A not only has the highest uptime but also achieves a balance between performance and savings, with a moderate failure rate of 3% and implementation time of 30 days. In contrast, Model D, while having the lowest cost savings of $15,000 and the highest failure rate of 7%, may require more time to implement, taking 50 days. This could be indicative of its complexity or resource requirements. Overall, Model E emerges as the most advantageous in terms of cost savings and reliability, while Model A offers the best uptime, making it crucial for decision-makers to weigh these factors based on their specific operational needs.

Model E is highlighted with the highest cost savings at $25,000, followed by Model A and Model C, which save $22,000 and $20,000, respectively (Figure 1). In terms of uptime, Model A leads with a percentage of 94%, closely followed by Model C at 92% and Model E at 91%. However, the failure rate reveals that Model E has the lowest at 2%, indicating its reliability. Conversely, Model D shows the lowest cost savings at $15,000 and the highest failure rate of 7%, suggesting that its performance may not justify the investment. Additionally, Model D requires the most implementation time at 50 days, which could impact its overall feasibility compared to the other models, particularly Model A, which takes only 30 days. Overall, the graph effectively conveys that while Model E excels in cost savings and reliability, Model A offers the best uptime with a relatively quick implementation, making it a strong candidate for operational considerations.

Table 2 shows the normalized data. The first column represents the first metric, where values range from approximately 0.4324 to 0.4618, indicating slight variation among the models. Model A (0.4618) shows the highest value in this metric, suggesting better performance in whatever aspect it represents, while Model D (0.4324) performs the lowest. In the second column, Model E (0.5487) leads, indicating superior performance, while Model B (0.4060) exhibits the weakest performance in this area. This disparity might suggest that Model E excels in the factor measured by this metric. The third column demonstrates a notable range, with Model D scoring the highest at 0.6897, indicating significant strength in this particular metric. Conversely, Model E (0.1971) reflects the weakest performance, suggesting that its overall effectiveness might be impacted in this aspect.

In this scenario, the four metrics might refer to various performance indicators, such as uptime, cost savings, failure rate, and implementation time. By assigning the same weight to each metric, the analysis underscores that no single factor should disproportionately influence the overall evaluation of the models. This methodology can be particularly useful in decision-making contexts where a holistic view is essential. However, while equal weights promote fairness in the assessment, they may not reflect real-world scenarios where certain metrics might hold more significance than others depending on specific organizational goals. For instance, in a highly competitive environment, uptime might be prioritized over cost savings, or vice versa, depending on the context. In summary, this uniform weighting system provides a clear framework for evaluating the models, ensuring a comprehensive assessment.

Table 1. Using AI for Predictive Maintenance.

DATA SET	Uptime (%)	Cost Savings ($)	Failure Rate (%)	Implementation Time (Days)
Model A	94	22,000	3	30
Model B	90	18,500	5	45
Model C	92	20,000	4	35
Model D	88	15,000	7	50
Model E	91	25,000	2	40

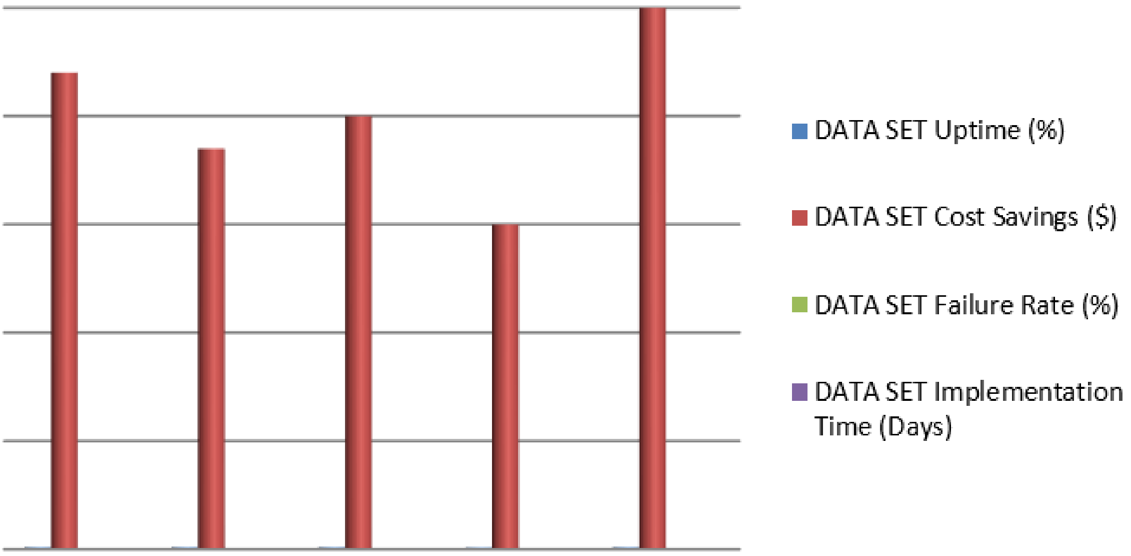

Fig. 1. Using AI for Predictive Maintenance.

Table 2. Normalized Data.

Normalized Data			
0.4618	0.4828173	0.295599	0.33
0.4422	0.4060055	0.492665	0.5
0.452	0.4389249	0.394132	0.39
0.4324	0.3291936	0.68973	0.55
0.4471	0.5486561	0.197066	0.44

Table 3 exhibits the weighted normalized DM. In the first row, Model A scores highest in the first two metrics with values of approximately 0.1155 and 0.1207, indicating strong performance in these areas. However, its score of 0.07 in the third metric suggests a significant weakness, which may impact its overall evaluation. Similarly, Model E shows promising results in the second metric with a score of 0.1372 but struggles in the third metric at 0.05. Model D exhibits the highest score in the third metric (0.17), reflecting its strengths in that specific area, while its overall performance is moderate, with a lower score in the first two metrics. This variation illustrates how different models excel in different aspects, making it crucial for decision-makers to analyze these strengths and weaknesses comprehensively. Ultimately, this matrix provides a nuanced understanding of model performance. Stakeholders can leverage these insights to make informed decisions, considering not just individual strengths but the overall balance of performance across all metrics.

Table 3. Weighted normalized DM.

Weighted normalized DM			
0.11546134	0.12070433	0.07	0.0826
0.11054809	0.10150137	0.12	0.1239
0.11300472	0.10973121	0.1	0.0963
0.10809147	0.08229841	0.17	0.1376
0.11177641	0.13716402	0.05	0.1101

Table 4 provides a table for the assessment value. Model E leads with an assessment value of 0.0896, indicating strong overall performance compared to the other models. This positive score suggests that Model E effectively meets the desired criteria and may offer the best return on investment, making it a prime candidate for implementation. Conversely, Model D has the lowest assessment value at -0.1197, highlighting significant shortcomings in its performance.

This negative value implies that Model D does not meet the required standards, and its adoption may lead to potential inefficiencies or increased costs. Similarly, Model B also presents a negative assessment value of -0.0350, suggesting that it may not be the best choice among the options available. Models A and C show positive values of 0.0797 and 0.0279, respectively, indicating they perform adequately but not as strongly as Model E.

Table 4. Assessment value.

	Assessment value
Model A	0.0796937
Model B	-0.0349751
Model C	0.02786867
Model D	-0.1196632
Model E	0.08957758

Table 5. Ranks.

Rank	
Model A	2
Model B	4
Model C	3
Model D	5
Model E	1

Table 5 and Figure 2 displays the ranks. Model A follow closely in second place, demonstrating solid performance that, while not as strong as Model E, still indicates a robust offering. This ranking suggests that Model A could be a viable alternative if Model E is not selected for some reason. Model C holds the third position, reflecting a commendable performance but not enough to surpass either Model A or E. The ranking signifies that it still offers a competitive advantage compared to lower-ranked models. In the lower ranks, Model B is placed fourth and Model D fifth, indicating that these models underperform relative to their counterparts. Model D's last-place ranking is particularly noteworthy, as it may signal critical deficiencies that could hinder operational effectiveness if chosen. Overall, this ranking system enables stakeholders to prioritize their choices, emphasizing the need to select models that deliver optimal performance and value for their specific requirements.

Model E is highlighted as the top performer with a rank of 1, illustrating its superiority among the options. This visual emphasis reinforces its position as the most favorable choice based on previous assessments. In contrast, Model D is ranked last with a score of 5, suggesting significant deficiencies in performance that warrant careful consideration before selection. Model A and Model C occupy the second and third ranks, respectively, showcasing strong performance but not quite reaching the level of Model E. The upward trend from Model A to Model C reflects a competitive evaluation, indicating that both models have commendable attributes, though they lag behind the leading model. Model B, ranked fourth, experiences a dip in rank compared to the others, suggesting it is less favorable in overall performance.

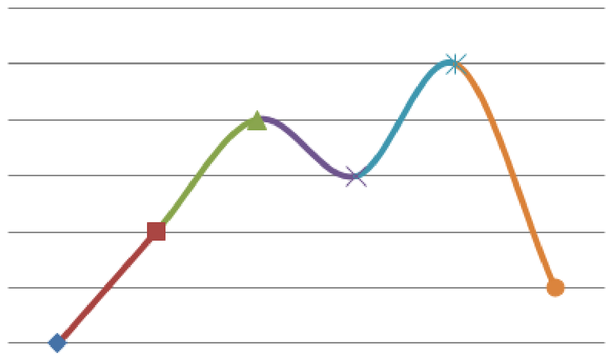

Fig. 2. A Rank diagram.

5. CONCLUSION

The integration of the Internet of Things (IoT) enables real-time data exchange, allowing effective use of condition monitoring data in predictive maintenance. By combining efficient data collection with integrated analysis, businesses can move from reactive to proactive maintenance strategies, thus optimizing operations and reducing costs. Image-based predictive maintenance has gained traction across multiple sectors, including construction and telecommunications, where drone surveys are utilized for structural monitoring. These innovations, driven by deep learning algorithms, enable routine inspections to detect potential problems before they develop into costly failures. Implementing a robust predictive maintenance strategy not only leads to cost savings, but also creates new revenue opportunities as high-value assets become more reliable. Artificial Intelligence (AI) is key to improving predictive maintenance systems. By automating the analysis of condition monitoring data, AI eliminates the need for manual assessments, thereby increasing operational efficiency. The techniques are essential for building models that predict equipment failures using historical data. This shift towards AI-driven predictive maintenance aligns with the future trajectory of the industry, where operations will become largely self-sufficient. In our study, we investigated the reliability of machine learning models powered by AI for predictive maintenance in electric submersibles. Using data from SCADA systems, we have developed several predictive maintenance models to evaluate their performance in failure prediction. A systematic literature review conducted as part of this study underscores the significant impact of machine learning and deep learning techniques on predictive maintenance strategies. These approaches improve situational awareness, improve operational efficiency and provide reliable maintenance solutions. As industries increasingly adopt predictive maintenance, the integration of AI technologies promises to deliver significant advantages, including reduced downtime, improved safety, and optimized asset management.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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