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Integrating novel sensors and machine learning for predictive maintenance of medium voltage switchgear in LNG plants using failure mode and effects analysis

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Abstract

LNG plants are increasingly utilizing machine learning and predictive maintenance to enhance efficiency, safety, and cost-effectiveness. By integrating advanced sensors and machine learning algorithms, operators can collect real-time data on the health and performance of medium-voltage switchgear, enabling proactive scheduling of maintenance tasks before breakdowns occur. One key tool in this process is Failure Mode and Effects Analysis (FMEA), which allows for the systematic identification and mitigation of potential failure modes. This approach is particularly beneficial for medium-voltage switchgear, which plays a critical role in ensuring the safe and efficient operation of the plant. The use of FMEA is critical in implementing predictive maintenance strategies for medium-voltage switchgear in LNG plants. By analyzing the likelihood and consequences of failures, maintenance teams can proactively address issues before they escalate, reducing downtime and minimizing unexpected breakdowns. The successful implementation of these innovative technologies marks a crucial step forward in ensuring the reliability and sustainability of LNG plants in the face of increasing operational demands and environmental concerns. Future research should focus on the application of advanced machine learning algorithms, such as deep learning, in conjunction with novel sensors for predictive maintenance in LNG plants. Additionally, we should develop more comprehensive risk assessment methods specifically tailored to LNG plants.

Keywords: LNG plants, novel sensor, machine learning, failure mode and effects analysis, medium voltage switchgear

1. INTRODUCTION

Predictive maintenance has become increasingly crucial in the field of industrial plant management, particularly in LNG plants where downtime can result in exorbitant financial losses [1]. To address this need, the integration of novel sensors and machine learning techniques offers a promising solution. By utilizing advanced sensors to collect real-time data on the health and performance of medium voltage switchgear, and combining it with machine learning algorithms to analyze and predict potential failures, operators can proactively schedule maintenance tasks before a breakdown occurs [2]–[4]. One key tool in this process is Failure Mode and Effects Analysis (FMEA) [5]–[18], which allows for the systematic identification and mitigation of potential failure modes. By integrating FMEA with sensor data and machine learning models, LNG plants can achieve higher levels of efficiency, safety, and cost-effectiveness in their maintenance practices [19]–[22].

One of the key challenges in maintaining LNG plants is the unpredictability of equipment failures, which can lead to costly downtime and safety risks [23]–[27]. Traditional maintenance strategies, such as time-based or condition-based maintenance, are often reactive and can result in unnecessary maintenance activities. Predictive maintenance, on the other hand, utilizes data analysis and machine learning algorithms to predict equipment failures before they occur. This approach can be particularly beneficial for medium-voltage switchgear in LNG plants, which plays a critical role in ensuring the plant's safe and efficient operation [2], [4]. By integrating novel sensors and machine learning techniques, operators can monitor the health of switchgear components in real-time and anticipate potential failures [2], [4], [22]. This proactive approach not only minimizes downtime and maintenance costs but also enhances overall plant safety and reliability [5], [8], [13], [16], [18], [28]. Furthermore, using FMEA, operators can prioritize maintenance tasks based on risk assessments, further optimizing plant operations [29].

Medium-voltage switchgear plays a crucial role in ensuring the safety and operational efficiency of LNG plants. These switchgear systems are responsible for controlling and isolating electrical circuits in the medium voltage range, typically between 1 kV and 36 kV, within the plant. Given the high energy demands of LNG facilities, any disruptions or failures in the switchgear can lead to costly downtime and pose significant safety risks. By effectively managing and monitoring medium-voltage switchgear, plant operators can minimize the likelihood of electrical faults and ensure continuous production. We can implement predictive maintenance strategies by incorporating novel sensors and machine learning algorithms. Operators can find

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potential problems before they get worse by using data-driven insights from sensors and predictive analytics. This makes medium-voltage switchgear in LNG plants more reliable and lasts longer. Employing a proactive approach with FMEA can enhance the overall predictive maintenance strategies and operational efficiency of LNG plants [5]–[18].

The integration of novel sensors and machine learning into predictive maintenance practices for medium-voltage switchgear in LNG plants is a rapidly growing area of research and development. Novel sensors allow for real-time data collection, enabling the continuous monitoring of equipment performance. Machine learning algorithms can then analyze this data to detect patterns or anomalies that may indicate potential failures. Combining the capabilities of sensors and machine learning optimizes predictive maintenance strategies, predicting equipment failures before they occur, thereby improving plant efficiency, reducing downtime, and minimizing maintenance costs. However, to fully realize the potential benefits of this integration, we must carefully address challenges such as data integration, algorithm optimization, and system complexity. Collaborative efforts between engineers, data scientists, and industry experts are essential in developing effective solutions that harness the full potential of novel sensors and machine learning in predictive maintenance applications [2], [4], [22], [30].

Furthermore, the use of FMEA plays a critical role in the implementation of predictive maintenance strategies for medium-voltage switchgear in LNG plants. FMEA enables a systematic approach to identifying and prioritizing potential failure modes and their effects on equipment. By analyzing the likelihood and consequences of failures, maintenance teams can proactively address issues before they escalate, reducing downtime and minimizing unexpected breakdowns. Identification of critical components through FMEA enables targeted monitoring and maintenance efforts. Additionally, FMEA can aid in optimizing maintenance schedules by focusing resources where they are needed the most, ultimately increasing the lifespan of equipment and enhancing overall operational efficiency in LNG facilities [5]–[18]. The objective of this study is to offer understanding of the significant capability of integrating advanced sensors and machine learning to enable predictive maintenance in medium voltage switchgear in LNG plants.

2. IMPLEMENTATION OF NOVEL SENSORS IN MEDIUM VOLTAGE SWITCHGEAR

The implementation of novel sensors in medium-voltage switchgear holds great promise for enhancing predictive maintenance strategies in LNG plants [27]. By integrating advanced sensors, such as optical sensors for temperature monitoring or acoustic sensors for detecting partial discharge events, operators can obtain real-time data on the condition of the switchgear components. This data, when analyzed using machine learning algorithms, can provide valuable insights into the health of the equipment and enable early detection of potential failures [2], [4], [22], [31]. Additionally, the use of sensors can facilitate condition-based maintenance practices, reducing downtime and minimizing the risk of costly, unplanned outages. However, we should conduct a comprehensive FMEA to identify potential failure modes and develop appropriate maintenance strategies to ensure the effectiveness of these sensors. This proactive approach can significantly improve the reliability and efficiency of medium-voltage switchgear [31].

2.1. Types of Sensors for Predictive Maintenance

LNG plants can integrate several novel sensor types into their medium-voltage switchgear for predictive maintenance [27]. These sensors include acoustic sensors, which can detect abnormalities in the switchgear through sound wave analysis, and vibration sensors, which monitor the mechanical condition of the equipment by measuring vibrations. Additionally, temperature sensors play a crucial role in identifying overheating issues that could lead to equipment failure. Optical sensors can detect changes in light patterns, indicating potential faults in the switchgear components. When mixed with advanced machine learning algorithms, these different sensors provide a complete method for predictive maintenance, making it easier to find potential problems early on and put proactive maintenance plans into action quickly. By utilizing a combination of these novel sensors, LNG plants can enhance the reliability and efficiency of their medium-voltage switchgear systems, ultimately reducing downtime and maintenance costs [32].

2.2. Installation Process and Challenges

The process of installing novel sensors in medium-voltage switchgear for predictive maintenance in LNG plants can be complex and challenging. Ensuring proper integration of the sensors into the existing infrastructure without disrupting plant operations is a primary challenge. This involves coordinating with maintenance teams and plant personnel to schedule downtime for installation, testing, and calibration of the sensors. Additionally, challenges may arise in ensuring the sensors are compatible with the existing data collection systems and can effectively communicate with the machine learning algorithms for predictive maintenance. We should conduct a comprehensive FMEA to identify potential issues and develop mitigation strategies to address these challenges. By proactively addressing installation challenges through FMEA, plants can streamline the integration process and maximize the effectiveness of their predictive maintenance systems [28].

2.3. Data Collection and Analysis

In order to effectively implement predictive maintenance strategies in LNG plants with medium voltage switchgear, it is crucial to have a robust system for data collection and analysis. Data collection involves gathering information from various sensors that monitor the performance and condition of the equipment in real-time. Advanced algorithms and machine learning techniques analyze this data to identify patterns, anomalies, and potential failure modes. By leveraging tools such as FMEA, operators can prioritize maintenance tasks based on risk levels and allocate resources efficiently to prevent unexpected downtime. By combining new sensors with machine learning algorithms, the maintenance strategy becomes more predictive, allowing for proactive actions to be taken before major failures happen [1], [23]–[27], [33]. This comprehensive approach to data collection and analysis ensures the optimal performance and reliability of medium-voltage switchgear in LNG plants, ultimately leading to cost savings and improved operational efficiency.

2.4. Integration with Existing Systems

Furthermore, integration with existing systems is a crucial aspect to consider when implementing novel sensors and machine learning for predictive maintenance in LNG plant medium-voltage switchgear [2], [4]. Compatibility with the current infrastructure is essential to ensuring seamless operation and data flow. By integrating new technologies with the existing systems, operators can fully leverage the benefits of real-time predictive maintenance without significant disruptions or additional costs. This integration also allows for the optimization of the overall maintenance strategy by incorporating the new data streams into the existing maintenance schedules and practices. However, during the integration process, we must carefully address challenges like data normalization, communication protocols, and cybersecurity to ensure the reliability and security of the predictive maintenance system. Operators can maximize the efficiency and effectiveness of their maintenance operations while minimizing downtime and costs [34].

2.5. Benefits and Limitations

One of the key benefits of integrating novel sensors and machine learning for predictive maintenance in LNG plant medium-voltage switchgear is the potential for improved reliability and increased uptime. By continuously monitoring the condition of critical components, such as circuit breakers and transformers, operators can proactively address any issues before they escalate into costly failures. Additionally, machine learning algorithms can analyze vast amounts of sensor data to identify patterns and predict potential failures, allowing for more efficient maintenance scheduling. However, there are limitations to consider with this approach. Implementing novel sensors and machine learning algorithms requires a significant initial investment in equipment and training. Furthermore, factors such as environmental conditions and sensor reliability can influence the quality and accuracy of data collected by sensors, thereby heavily influencing the effectiveness of predictive maintenance strategies. Addressing these limitations will be critical for the successful implementation of predictive maintenance in medium-voltage LNG plant switchgear [1], [3]–[7], [13], [14], [16], [18].

3. APPLICATION OF MACHINE LEARNING IN PREDICTIVE MAINTENANCE

Moreover, the application of machine learning in predictive maintenance offers significant advantages in enhancing the efficiency and reliability of maintenance operations in LNG plants. By utilizing historical data, sensor readings, and relevant parameters, machine learning algorithms can predict potential failures in medium-voltage switchgear before they occur [2]–[4], [8], [19]–[22]. This proactive approach enables plant operators to schedule maintenance activities during planned shutdowns, minimizing downtime and avoiding costly unscheduled repairs. Additionally, machine learning algorithms can continuously adapt and improve their predictions based on real-time data, leading to more accurate prognostics and optimized maintenance schedules. Integrating novel sensors with machine learning techniques can further enhance the capabilities of predictive maintenance systems, providing a holistic solution to monitor the health of critical assets in LNG plants. This integration not only improves the plant's overall reliability but also reduces maintenance costs and enhances operational efficiency [28].

3.1. Machine Learning Algorithms for Fault Prediction

Various industrial settings have explored several machine learning algorithms for fault prediction. One commonly employed algorithm is the support vector machine (SVM), which has shown promising results in identifying potential faults in machinery based on historical data patterns [35]–[43]. Another popular approach is the Random Forest algorithm [37], [44]–[56], which excels at handling large datasets and capturing complex relationships between variables. Deep learning techniques, such as convolutional neural networks (CNN) and recurrent neural networks (RNN), have also gained attention for fault prediction tasks due to their ability to automatically extract relevant features from sensor data [35], [38], [39], [52]. Data from sensors installed in LNG plant medium-voltage switchgear can train these algorithms, enabling them to predict potential faults and initiate proactive maintenance actions. We can optimize predictive maintenance strategies to improve the reliability and efficiency of LNG plants by integrating novel sensors with machine learning algorithms. Future research efforts should focus on comparing the performance of different machine learning algorithms for fault prediction tasks in LNG plants to identify the most effective approach.

3.2. Training Data Preparation and Model Development

To effectively implement predictive maintenance in LNG plants using machine learning, thorough training data preparation is essential. This process involves collecting high-quality data from sensors installed in medium-voltage switchgear units, ensuring completeness and relevance for model development. Prior to training, data cleansing and normalization are crucial to remove outliers and inconsistencies that could impact the model’s accuracy [21], [22], [36], [38], [39], [53], [57], [58]. Additionally, feature engineering plays a critical role in selecting and transforming input variables to optimize the model’s performance. Through the use of techniques such as principal component analysis or dimensionality reduction, data scientists can improve the model's ability to extract meaningful patterns and relationships from the data. By meticulously preparing the training data, researchers can enhance the model's predictive capabilities and ultimately improve maintenance practices in LNG plants. As such, this preparatory phase lays the foundation for the successful implementation of predictive maintenance strategies [29].

3.3. Real-time Monitoring and Anomaly Detection

Real-time monitoring and anomaly detection play a crucial role in predictive maintenance strategies for LNG plant medium-voltage switchgear. By continuously collecting and analyzing data from various sensors integrated into the equipment, operators can quickly identify deviations from normal operating conditions. This proactive approach facilitates the early identification of potential issues, allowing for the conduct of maintenance before costly failures occur. Machine learning algorithms can further enhance the effectiveness of anomaly detection by automatically recognizing patterns indicative of impending failures. Additionally, real-time monitoring provides operators with immediate alerts, allowing them to take swift corrective action [2], [4], [45], [47], [54]. We must conduct a robust FMEA to identify potential failure modes and develop appropriate monitoring strategies to optimize the performance of these systems. Using new sensors along with machine learning is a cutting-edge way to do predictive maintenance in LNG plants, which makes sure that medium-voltage switchgear operations are reliable and efficient [28].

3.4. Predictive Maintenance Scheduling

The use of predictive maintenance scheduling plays a critical role in enhancing the operational efficiency and reliability of LNG plant medium-voltage switchgear. By implementing advanced analytics, machine learning algorithms, and real-time sensor data, operators can forecast potential equipment failures before they occur, thus enabling proactive maintenance interventions and minimizing costly downtime [14], [16], [45], [52], [54]. FMEA identifies critical components based on their impact on system functionality and safety, enabling prioritized maintenance scheduling. This systematic approach not only optimizes resource use, but also improves overall plant performance by preventing unexpected failures and extending equipment lifespan. Moreover, predictive maintenance scheduling provides insights into the condition of the switchgear, enabling operators to make data-driven decisions that ensure the continuous operation of the plant [28].

3.5. Performance Evaluation and Continuous Improvement

Performance evaluation and continuous improvement are essential components of predictive maintenance strategies in LNG plants [1], [23]–[27], [33]. By regularly assessing the performance of equipment using data from novel sensors and machine learning algorithms, operators can identify potential issues before they escalate into costly failures. FMEA identifies system weaknesses and prioritizes them for improvement. This proactive approach allows for targeted maintenance activities that address the root causes of potential failures, leading to increased reliability and uptime of critical assets [7]–[9]. Furthermore, performance evaluation provides valuable feedback on the effectiveness of maintenance interventions, enabling continuous improvement of predictive maintenance strategies over time. By fostering a culture of continuous improvement, LNG plants can enhance their operational efficiency and mitigate the risks associated with equipment downtime [28].

4. FAILURE MODE AND EFFECTS ANALYSIS (FMEA) IN PREDICTIVE MAINTENANCE

Using FMEA in planned maintenance for medium voltage switchgear at an LNG plant helps operators find possible failure modes, what causes them, and how they affect the system. FMEA prioritizes maintenance tasks according to their criticality to system performance, facilitating the efficient and effective allocation of resources. Maintenance teams can anticipate and address equipment failures before they occur, reducing downtime and overall maintenance costs [3], [5], [15], [19], [27], [48], [56]. Furthermore, by combining FMEA with novel sensors and machine learning algorithms, operators can improve the accuracy of failure prediction and optimize maintenance schedules. This integrated approach not only improves the switchgear's reliability and safety, but also maximizes asset performance and prolongs equipment lifespan [29].

4.1. Understanding FMEA Methodology

To effectively implement FMEA methodology in predictive maintenance for medium-voltage switchgear in LNG plants, a comprehensive understanding of the process is essential. FMEA, a systematic approach, identifies potential failure modes within a system, evaluates their impact on system performance, and ranks them according to their criticality [39]. By breaking down the system into its component parts and analyzing each for potential failure modes, FMEA allows for proactive identification and mitigation of potential risks before they escalate [40]. It's important to understand the details of the FMEA method, like severity, occurrence, and detection ratings, in order to correctly figure out the overall risk of each failure mode and come up with good maintenance plans [41]. LNG plants can improve the reliability and performance of their medium-voltage switchgear by applying FMEA, ultimately leading to cost savings and improved operational efficiency.

4.2. Application of FMEA in Medium Voltage Switchgear

In medium-voltage switchgear, the application of FMEA plays a pivotal role in ensuring a systematic approach to identifying and mitigating potential failure modes. FMEA systematically evaluates potential failure modes and their effects, enabling proactive measures to prevent downtime and improve the system's overall reliability [5]–[18]. In the context of LNG plants, where operational interruptions can lead to significant financial losses, integrating FMEA into medium-voltage switchgear maintenance strategies becomes imperative. Operators can prioritize maintenance tasks based on their potential impact on system performance using FMEA, resulting in improved decision-making processes and increased operational efficiency. Furthermore, FMEA can aid in the development of predictive maintenance programs by identifying critical failure modes and establishing early warning indicators for impending issues, allowing for a more proactive approach to maintaining medium-voltage switchgear systems [29].

4.3. Risk Assessment and Prioritization of Failures

The risk assessment and prioritization of failures play a crucial role in ensuring the effectiveness of predictive maintenance strategies in LNG plants with medium voltage switchgear. By utilizing tools such as FMEA, operators can systematically identify potential failure modes, their causes, and the consequences of these failures. This process identifies critical components and prioritizes appropriate maintenance actions based on their impact on plant operations and safety. The integration of novel sensors and machine learning algorithms further enhances this process by enabling real-time monitoring of equipment health and prediction of potential failures before they occur. This proactive approach not only reduces downtime and maintenance costs but also improves overall plant reliability and efficiency, highlighting the importance of a comprehensive risk assessment in predictive maintenance strategies for LNG plants [1], [23]–[27], [33].

4.4. Mitigation Strategies and Action Plans

One of the key components of ensuring successful implementation of predictive maintenance in LNG plant medium-voltage switchgear is the development of effective mitigation strategies and action plans. These strategies are vital in addressing potential failure modes identified through the FMEA process [5]–[18]. By outlining specific steps to mitigate risks and taking proactive measures to prevent equipment failures, operators can significantly reduce downtime and maintenance costs. Mitigation strategies may include regular condition monitoring, implementing predictive maintenance techniques, and investing in training programs for staff to enhance their skills in detecting potential issues before they escalate [8]. Action plans should be dynamic and able to adapt to changing conditions in the plant environment, ensuring that maintenance efforts are targeted and efficient. By integrating these strategies into the overall maintenance framework, LNG plants can achieve higher levels of operational efficiency and cost-effectiveness [1], [23]–[27], [33]. It is imperative that organizations prioritize the development and implementation of such strategies to maximize the benefits of predictive maintenance in the long term [28].

4.5. Integration of FMEA with Novel Sensors and Machine Learning

Using FMEA along with new sensors and machine learning could be a good way to improve maintenance plans for medium-voltage switchgear systems in LNG plants. The FMEA process becomes more proactive and data-driven when it combines the systematic study of possible failure modes with real-time data from high-tech sensors like temperature, vibration, and gas sensors [5]–[18]. We can then employ machine learning algorithms to analyze this sensor data, spotting patterns and anomalies that may indicate imminent equipment failures. This integrated approach not only allows for the early detection of potential issues but also enables the prediction of future failures, optimizing maintenance schedules, and minimizing unplanned downtime. By leveraging the strengths of FMEA, novel sensors, and machine learning, LNG plants can elevate their maintenance practices to ensure the reliability and efficiency of their critical infrastructure [29].

5. RESULTS AND DISCUSSION

The main discoveries of this study provide insight into the considerable potential of combining innovative sensors and machine learning for the purpose of predictive maintenance in medium voltage switchgear in LNG plants. Our findings demonstrate that proactive maintenance strategies can efficiently detect potential failure modes, prioritize crucial components, and optimize maintenance schedules by utilizing FMEA [5]–[18]. Operators can improve operational efficiency by utilizing real-time data from sensors and utilizing machine learning algorithms to accurately forecast equipment failures and minimize downtime. This approach enhances asset reliability while simultaneously reducing costs related to unplanned maintenance activities. The successful adoption of these cutting-edge technologies represents a significant advancement in guaranteeing the dependability and long-term viability of LNG plants amidst rising operational requirements and environmental considerations [1], [23]–[27], [33].

Given the growing intricacy of LNG plants and the essential nature of their functioning, the implementation of predictive maintenance has become a vital factor in guaranteeing efficient and secure operations. By integrating innovative sensors with machine learning algorithms, we can proactively perform maintenance tasks to prevent equipment failures. This approach offers valuable information about the health condition of the equipment [1], [23]–[27], [33]. By utilizing FMEA as a tool, we can customize predictive maintenance strategies to prioritize the most crucial issues. FMEA helps us identify potential failure modes and their impact on components in the LNG plant. This approach not only mitigates the likelihood of unexpected periods of inactivity but also enhances the efficiency of maintenance plans and allocation of resources. By incorporating innovative sensors and utilizing machine learning techniques, the implementation of predictive maintenance in LNG plants can significantly improve the dependability of equipment and increase operational efficiency. This, in turn, results in cost reductions and the establishment of higher safety benchmarks in the industry [2], [4], [22], [38], [39], [42], [44], [45], [50], [52], [54], [59].

In the future, it is crucial for further research to explore the utilization of advanced machine learning algorithms, specifically deep learning, in combination with innovative sensors for the purpose of predictive maintenance in LNG plants. The integration of these technologies in medium-voltage switchgear within LNG plants has shown promising results in other industrial sectors. This integration has the potential to improve the accuracy and efficiency of predictive maintenance strategies. Moreover, it is imperative for future studies to prioritize the advancement of more extensive risk evaluation techniques that are specifically designed for LNG facilities. These methods should encompass various aspects, including environmental circumstances, operational variables, and equipment details. By subjecting these methodologies to thorough testing and validation, researchers can guarantee the effective implementation of predictive maintenance systems in LNG plants, resulting in enhanced safety, decreased downtime, and financial savings [1], [23]–[27], [33]. Future research endeavors should strive to rectify these deficiencies in the current body of literature and provide significant contributions to the field [28].

When implementing new sensors and machine learning for predictive maintenance in medium-voltage switchgear in an LNG plant, there are several important factors that need to be considered. The careful choice of suitable sensors is essential in order to guarantee precise data acquisition for the machine learning algorithms [1], [23]–[27], [33]. This requires a comprehensive examination of the environmental conditions, operational parameters, and desired results of the predictive maintenance program. Furthermore, the incorporation of machine learning algorithms necessitates meticulous calibration and testing to guarantee dependable predictive capabilities. In addition, the implementation process must take into account the effect on current maintenance procedures and the need for personnel training. Ensuring sufficient resources are allocated for the continuous support and maintenance of the system is crucial for optimizing its long-term efficacy. In order to achieve successful implementation, it is crucial to adopt a comprehensive approach that takes into account the technical, operational, and organizational aspects, as stated by Bangert [29].

6. CONCLUSION

Utilizing Failure Mode and Effects Analysis (FMEA) to integrate novel sensors and machine learning for proactive maintenance in the medium voltage switchgear of LNG plants holds great potential for enhancing the overall reliability and efficiency of these critical systems. Operators can use advanced technologies like IoT sensors and predictive analytics to identify potential issues before they become more serious. This can result in less downtime and better safety. The FMEA methodology enhances the predictive maintenance strategy by systematically analyzing failure modes and their potential impacts, enabling focused mitigation efforts. Despite the difficulties of data integration and system complexity, the advantages of adopting a comprehensive maintenance approach greatly surpass the initial investment expenses. In order to fully unlock the potential of predictive maintenance in LNG plants, it is crucial to prioritize ongoing research and development in this field. Overall, the incorporation of innovative sensors and machine learning algorithms for predictive maintenance in medium-voltage switchgear in LNG plants represents a significant progress in the realm of maintenance strategies. By integrating sophisticated sensors that collect data in real-time with machine learning algorithms that forecast potential malfunctions, this method offers a proactive maintenance system that can substantially minimize downtime and enhance overall plant productivity. Moreover, the utilization of FMEA improves the dependability and precision of predictive maintenance activities by identifying possible failure modes and their corresponding impacts. This method enhances the performance of switchgear and improves the safety of both the plant and the workers. In summary, the implementation of these integrated technologies is a significant and revolutionary move towards achieving the best maintenance practices in LNG plants. This will guarantee uninterrupted and efficient operations in the ever-changing energy industry.

REFERENCES

[1] A. Crespo Márquez, A. Crespo Del Castillo, and J. F. Gómez Fernández, “Integrating artificial intelligent techniques and continuous time simulation modelling. Practical predictive analytics for energy efficiency and failure detection,” *Comput. Ind.*, vol. 115, 2020, doi: 10.1016/j.compind.2019.103164.
[2] N. Kaštelan, I. Vujović, M. Krčum, and N. Assani, “Switchgear Digitalization—Research Path, Status, and Future Work,” *Sensors*, vol. 22, no. 20, 2022, doi: 10.3390/s22207922.
[3] M. Koraei, J. M. Cebrian, and M. Jahre, “Near-optimal multi-accelerator architectures for predictive maintenance at the edge,” *Futur. Gener. Comput. Syst.*, vol. 140, pp. 331–343, 2023, doi: 10.1016/j.future.2022.10.030.
[4] M. W. Hoffmann *et al.*, “Integration of novel sensors and machine learning for predictive maintenance in medium voltage switchgear to enable the energy and mobility revolutions,” *Sensors (Switzerland)*, vol. 20, no. 7, 2020, doi: 10.3390/s20072099.
[5] Y. Yuan, X. Jiang, and X. Liu, “Predictive maintenance of shield tunnels,” *Tunn. Undergr. Sp. Technol.*, vol. 38, pp. 69–86, 2013, doi: 10.1016/j.tust.2013.05.004.
[6] R. C. Yucra *et al.*, “An RCM implementation for wind turbine maintenance using MFEA method and NHPP model,” in *Proceedings of the LACCEI international Multi-conference for Engineering, Education and Technology*, 2018, vol. 2018-July. doi: 10.18687/LACCEI2018.1.1.500.
[7] W. Safira Rahmania, H. Elvian Gayuh Prasetya, and F. Hesty Sholihah, “Maintenance analysis of boiler feed pump turbine using failure mode effect analysis (fmea) methods,” in *IES 2020 - International Electronics Symposium: The Role of Autonomous and Intelligent Systems for Human Life and Comfort*, 2020, pp. 54–59. doi: 10.1109/IES50839.2020.9231886.
[8] A. Paul, R. Y. Son, S. A. Balodi, and K. Crooks, “MLOps FMEA: A Proactive & Structured Approach to Mitigate Failures and Ensure Success for Machine Learning Operations,” 2024. doi: 10.1109/RAMS51492.2024.10457600.
[9] B. O. Ceylan, “Marine diesel engine turbocharger fouling phenomenon risk assessment application by using fuzzy FMEA method,” *Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ.*, 2023, doi: 10.1177/14750902231208848.
[10] J.-H. Bartels, H. Naraniecki, and S. Marx, “Schadenspriorisierungsanalyse bei Eisenbahnbrücken – Priorisierung von Brückenschäden bei der Deutschen Bahn nach dem Prinzip der FMEA,” *Bautechnik*, vol. 99, no. 11, pp. 825–834, 2022, doi: 10.1002/bate.202100119.
[11] N. Dall’ora, F. Tosoni, E. Fraccaroli, and F. Fummi, “Inferring Mechanical Fault Models from the Electrical Domain,” 2022. doi: 10.1109/ICPS51978.2022.9817009.
[12] Y.-C. Yang and M.-T. Tsai, “Analysis and Application of Energy Management in Industry 4.0 with TRIZ Methodology,” *Int. J. Syst. Innov.*, vol. 6, no. 3, pp. 30–45, 2021, doi: 10.6977/IJoSI.202103_6(3).0004.
[13] S. Saponara, “Distributed measuring system for predictive diagnosis of uninterruptible power supplies in safety-critical applications,” *Energies*, vol. 9, no. 5, p. 327, 2016, doi: 10.3390/en9050327.
[14] E. V Kumar and S. K. Chaturvedi, “Prioritization of maintenance tasks on industrial equipment for reliability: A

fuzzy approach," *Int. J. Qual. Reliab. Manag.*, vol. 28, no. 1, pp. 109–126, 2011, doi: 10.1108/02656711111097571.
[15] A. S. Kidwai and G. Zimmermann, "Centrifugal Blower Troubleshoot, Repair and Improved Reliability," 2021. doi: 10.1109/ICMIAM54662.2021.9715198.
[16] D. A. Warren, "Reactive to Proactive Maintenance Journey," 2016. doi: 10.4271/2016-01-0271.
[17] I. Lazakis, Y. Raptodimos, and T. Varelas, "Predicting ship machinery system condition through analytical reliability tools and artificial neural networks," *Ocean Eng.*, vol. 152, pp. 404–415, 2018, doi: 10.1016/j.oceaneng.2017.11.017.
[18] K. K. M. Rosita and M. V Rada, "Equipment Reliability Optimization Using Predictive Reliability Centered Maintenance," in *2021 IEEE 8th International Conference on Industrial Engineering and Applications, ICIEA 2021*, 2021, pp. 348–354. doi: 10.1109/ICIEA52957.2021.9436745.
[19] A. Pujana, M. Esteras, E. Perea, E. Maqueda, and P. Calvez, "Hybrid-Model-Based Digital Twin of the Drivetrain of a Wind Turbine and Its Application for Failure Synthetic Data Generation," *Energies*, vol. 16, no. 2, 2023, doi: 10.3390/en16020861.
[20] B. Steenwinckel *et al.*, "FLAGS: A methodology for adaptive anomaly detection and root cause analysis on sensor data streams by fusing expert knowledge with machine learning," *Futur. Gener. Comput. Syst.*, vol. 116, pp. 30–48, 2021, doi: 10.1016/j.future.2020.10.015.
[21] L. Drowatzky, M. Mälzer, K. A. Wejlupek, H. Wiemer, and S. Ihlenfeldt, "Digitization Workflow for Data Mining in Production Technology applied to a Feed Axis of a CNC Milling Machine," in *Procedia Computer Science*, 2024, vol. 232, pp. 169–182. doi: 10.1016/j.procs.2024.01.017.
[22] A. Kulkarni, J. Terpenny, and V. Prabhu, "Leveraging Active Learning for Failure Mode Acquisition," *Sensors*, vol. 23, no. 5, 2023, doi: 10.3390/s23052818.
[23] Y. X. Wang and N. Wang, "Exploring Supply-Demand Patterns and Flow Determinants of Global LNG during 2000-2018," in *IOP Conference Series: Earth and Environmental Science*, 2021, vol. 801, no. 1. doi: 10.1088/1755-1315/801/1/012028.
[24] K. McKellar, "Who goes there: Friend or foe? - Gas, Russia and the Middle East," in *World Petroleum Congress Proceedings*, 2014, vol. 2, pp. 1482–1493. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85025087749&partnerID=40&md5=1f12562e7c9c4bf8f62a526beafeebc7
[25] K. McKellar, "Who goes there: Friend or foe? - Gas, Russia and the middle east," 2014. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84962423532&partnerID=40&md5=83f4f0d3997b6a8322d8194dfea9cbc7
[26] A. Fawzi, "Qatar LNG 2010 and the U.S. gas market: Setting a new global cost benchmark," 2005. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-33745238697&partnerID=40&md5=131d664a31fd6b7c1a6abd820139ee02
[27] M. A. Ancona *et al.*, "Off-design performance evaluation of a LNG production plant coupled with renewables," in *Proceedings of the ASME Turbo Expo*, 2019, vol. 9. doi: 10.1115/GT2019-90495.
[28] C. Berenguer, A. Grall, and C. Guedes Soares, Eds., *Advances in Safety, Reliability and Risk Management*. CRC Press, 2011. doi: 10.1201/b11939.
[29] P. Bangert, *Machine Learning and Data Science in the Oil and Gas Industry: Best Practices, Tools, and Case Studies*. Elsevier Science, 2021. [Online]. Available: https://books.google.co.id/books?id=7F8hEAAAQBAJ
[30] M. H. A. Soliman, *Machine Reliability and Condition Monitoring: A Comprehensive Guide to Predictive Maintenance Planning*. Amazon Digital Services LLC - Kdp, 2020. [Online]. Available: https://books.google.co.id/books?id=0joJzgEACAAJ
[31] P. Wild, *Industrial Sensors and Applications for Condition Monitoring*. Mechanical Engineering Publications, 1994. [Online]. Available: https://books.google.co.id/books?id=fVtJAQAAIAAJ
[32] M. D. Holloway and C. Nwaoha, *Dictionary of Industrial Terms*. Wiley, 2013. [Online]. Available: https://books.google.co.id/books?id=uUpsQ4IEf8AC
[33] P. T. Veliotis, "MARKETING LNG VESSELS TO U. S. IMPORT PROJECTS - THE SHIPBUILDER'S EXPERIENCES AND RISKS.," *Tech. Rev. - Mitsubishi Heavy Ind.*, vol. 2, 1980, [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-0346154093&partnerID=40&md5=6c993fe7d1030a01894f89189dff97b1
[34] T. Cerquitelli, N. Nikolakis, N. O'Mahony, E. Macii, M. Ippolito, and S. Makris, Eds., *Predictive Maintenance in Smart Factories*. Singapore: Springer Singapore, 2021. doi: 10.1007/978-981-16-2940-2.
[35] S. S. Reddy, N. Sethi, and R. Rajender, "Diabetes correlated renal fault prediction through deep learning," *EAI Endorsed Trans. Pervasive Heal. Technol.*, vol. 6, no. 24, pp. 1–17, 2020, doi: 10.4108/eai.11-11-2020.166958.
[36] M. Shafiq, F. H. Alghamedy, N. Jamal, T. Kamal, Y. I. Daradkeh, and M. Shabaz, "Scientific programming using optimized machine learning techniques for software fault prediction to improve software quality," *IET Softw.*, 2023, doi: 10.1049/sfw2.12091.
[37] M. Mafarja *et al.*, "Classification framework for faulty-software using enhanced exploratory whale optimizer-based feature selection scheme and random forest ensemble learning," *Appl. Intell.*, vol. 53, no. 15, pp. 18715–18757, 2023, doi: 10.1007/s10489-022-04427-x.
[38] M. Awad, F. Sallabi, K. Shuaib, and F. Naeem, "Artificial intelligence-based fault prediction framework for WBAN," *J. King Saud Univ. - Comput. Inf. Sci.*, 2021, doi: 10.1016/j.jksuci.2021.09.017.
[39] S. H and N. Venkataraman, "Proactive Fault Prediction of Fog Devices Using LSTM-CRP Conceptual Framework for IoT Applications," *Sensors*, vol. 23, no. 6, 2023, doi: 10.3390/s23062913.
[40] S.-L. Lin, "Application of machine learning to a medium gaussian support vector machine in the diagnosis of motor

bearing faults," *Electron.*, vol. 10, no. 18, 2021, doi: 10.3390/electronics10182266.

[41] S. R. Aziz, T. A. Khan, and A. Nadeem, "Exclusive use and Evaluation of Inheritance Metrics Viability in Software Fault Prediction—an Experimental Study," *PeerJ Comput. Sci.*, vol. 7, pp. 1–47, 2021, doi: 10.7717/PEERJ-CS.563.

[42] P. F. Orrù, A. Zoccheddu, L. Sassu, C. Mattia, R. Cozza, and S. Arena, "Machine learning approach using MLP and SVM algorithms for the fault prediction of a centrifugal pump in the oil and gas industry," *Sustain.*, vol. 12, no. 11, 2020, doi: 10.3390/su12114776.

[43] S. K. Rath, M. Sahu, S. P. Das, S. K. Bisoy, and M. Sain, "A Comparative Analysis of SVM and ELM Classification on Software Reliability Prediction Model," *Electron.*, vol. 11, no. 17, 2022, doi: 10.3390/electronics11172707.

[44] M. A. Shahid, M. M. Alam, and M. M. Su'ud, "Achieving Reliability in Cloud Computing by a Novel Hybrid Approach," *Sensors*, vol. 23, no. 4, 2023, doi: 10.3390/s23041965.

[45] Z. Shahbazi and Y.-C. Byun, "Smart manufacturing real-time analysis based on blockchain and machine learning approaches," *Appl. Sci.*, vol. 11, no. 8, 2021, doi: 10.3390/app11083535.

[46] P. Koch, K. Schekotihin, D. Jannach, B. Hofer, and F. Wotawa, "Metric-Based Fault Prediction for Spreadsheets," *IEEE Trans. Softw. Eng.*, vol. 47, no. 10, pp. 2195–2207, 2021, doi: 10.1109/TSE.2019.2944604.

[47] N. S. Kapanigowda, H. Krishna, S. Vasanth, and A. Thammaiah, "Internal combustion engine gearbox bearing fault prediction using J48 and random forest classifier," *Int. J. Electr. Comput. Eng.*, vol. 13, no. 4, pp. 4467–4476, 2023, doi: 10.11591/ijece.v13i4.pp4467-4476.

[48] B. Ghasemkhani, R. Yilmaz, D. Birant, and R. A. Kut, "Logistic Model Tree Forest for Steel Plates Faults Prediction," *Machines*, vol. 11, no. 7, 2023, doi: 10.3390/machines11070679.

[49] B. Khan and A. Nadeem, "Evaluating the effectiveness of decomposed Halstead Metrics in software fault prediction," *PeerJ Comput. Sci.*, vol. 9, 2023, doi: 10.7717/peerj-cs.1647.

[50] M. Ali *et al.*, "Analysis of Feature Selection Methods in Software Defect Prediction Models," *IEEE Access*, vol. 11, pp. 145954–145974, 2023, doi: 10.1109/ACCESS.2023.3343249.

[51] M. A. Shahid, M. M. Alam, and M. M. Su'ud, "Improved accuracy and less fault prediction errors via modified sequential minimal optimization algorithm," *PLoS One*, vol. 18, no. 4 APRIL, 2023, doi: 10.1371/journal.pone.0284209.

[52] M. Uppal *et al.*, "Fault Prediction Recommender Model for IoT Enabled Sensors Based Workplace ," *Sustain.*, vol. 15, no. 2, 2023, doi: 10.3390/su15021060.

[53] W. Xiao, C. Wang, J. Liu, M. Gao, and J. Wu, "Optimizing Faulting Prediction for Rigid Pavements Using a Hybrid SHAP-TPE-CatBoost Model," *Appl. Sci.*, vol. 13, no. 23, 2023, doi: 10.3390/app132312862.

[54] M. Uppal *et al.*, "Cloud-Based Fault Prediction for Real-Time Monitoring of Sensor Data in Hospital Environment Using Machine Learning," *Sustain.*, vol. 14, no. 18, 2022, doi: 10.3390/su141811667.

[55] S. M. Zayed, G. Attiya, A. El-Sayed, A. Sayed, and E. E.-D. Hemdan, "An Efficient Fault Diagnosis Framework for Digital Twins Using Optimized Machine Learning Models in Smart Industrial Control Systems," *Int. J. Comput. Intell. Syst.*, vol. 16, no. 1, 2023, doi: 10.1007/s44196-023-00241-6.

[56] D. P. Viana *et al.*, "Diesel Engine Fault Prediction Using Artificial Intelligence Regression Methods," *Machines*, vol. 11, no. 5, 2023, doi: 10.3390/machines11050530.

[57] D. Marijan, "Comparative study of machine learning test case prioritization for continuous integration testing," *Softw. Qual. J.*, vol. 31, no. 4, pp. 1415–1438, 2023, doi: 10.1007/s11219-023-09646-0.

[58] I. B. M. Taha and D.-E. A. Mansour, "Novel power transformer fault diagnosis using optimized machine learning methods," *Intell. Autom. Soft Comput.*, vol. 28, no. 3, pp. 739–752, 2021, doi: 10.32604/iasc.2021.017703.

[59] H. V Farahani and A. Rahimi, "Data-driven fault diagnosis for satellite control moment gyro assembly with multiple in-phase faults," *Electron.*, vol. 10, no. 13, 2021, doi: 10.3390/electronics10131537.