Predictive Maintenance in WSN based on Machine Learning

Shweta Sharma[1], Shailja Agnihotri[2]

[1]Assistant Professor,
Goswami Ganesh Dutta Sanatan Dharma College, Chandigarh, India,
shweta.sharma@ggdsd.ac.in

[2]Assistant Professor,
Goswami Ganesh Dutta Sanatan Dharma College, Chandigarh, India,
shailja@ggdsd.ac.in

Abstract:
Predictive maintenance is one of the key concerns in the field of wireless sensor networks. The purpose of predictive maintenance is to reduce unplanned energy consumption, to increase lifetime of the network and to reduce costs and delays. Predictive maintenance system is a new concept that aids the system to monitor and evaluate the status of those systems for which they are being developed. They also assist in maintaining the actions of these systems by predicting the future quality. With applications in industrial monitoring, smart cities and environmental sensing, the integration of AI and predictive maintenance in WSNs presents a promising path towards intelligent, economical, and scalable network management. In order to tackle the issues of sensor failures, network instability and system deterioration, this paper investigates the predictive maintenance in WSNs and along with the predictive maintenance and machine learning concepts.

***Keywords*: Artificial Intelligence, Machine Learning, Predictive maintenance system, Wireless Sensor Networks.**

(Article history: Selected from 3rd NICEDT 2025, Ropar, 14-15 Feb 2025)

I. INTRODUCTION

Predictive maintenance is service that keeps an eye on the functionality and state of a piece of machinery while it is in use to lower the likelihood of failure. Predictive maintenance's major goal is to spot possible production problems before they result in machine downtime. This is accomplished through continuous equipment performance monitoring made possible by sensors, data gathering, and close to real-time equipment and software communication. To perform the predictive maintenance, some key factors are required such as data collection and preparation, early defect identification, time to failure forecasting, maintenance planning, and resource planning. Predictive maintenance makes use of data analysis to spot any equipment flaws and operating irregularities, allowing for prompt fixes before problems arise. In order to reduce needless preventative maintenance expenses and unexpected outages, it seeks to minimize the frequency of maintenance.

Researchers and real-time developers have always been interested in WSN. One of the most important components in the creation and alterations of the WSN architecture is the battery. It is more fascinating to work on when the active and sleep modes are synchronized because if they are not, the node that is in the sleep state may never wake up and the true utilization is not achieved. Furthermore, proper route finding will result in reduced power consumption and the sensor node's battery life being at its best, which will ultimately contribute to an ideal network lifetime. When it comes to assessing the network node's sustainability, battery is an essential component. The node is referred to be an active node as long as it has power remaining. Since the battery cannot be charged throughout the simulation, it is crucial to use each watt (w) correctly. To save energy and battery, a node is kept in sleep mode while it is not taking part in a transfer event [1-6].

Real-time monitoring of several parameters is made possible by WSNs, which are made up of spatially dispersed sensors that gather and send data. Predictive maintenance uses this data to anticipate equipment breakdowns before they happen by incorporating machine learning algorithms. This proactive strategy increases asset longevity, lowers maintenance costs, and minimizes downtime. The precision and effectiveness of predictive maintenance plans in WSNs are improved by sophisticated models and methodologies such as anomaly detection and real-time data analysis. In the end, this collaboration between predictive maintenance and WSNs creates more intelligent and robust systems for a variety of industries.

II. MACHINE LEARNING

The goal of the machine learning, a domain of artificial intelligence (AI) is to create algorithms which let the computers learn from past data and make predictions or judgements. It is similar to educating a computer to identify trends and make wise decisions without having to be specifically programmed for every case that could arise. Significant Ideas in Machine Learning:

A. Learning Under Supervision

Each training example has an output label; therefore, the algorithm is taught on a labelled dataset. Regression and classification are frequent tasks.

B. Unsupervised Learning

The algorithm operates on data without output labels. It looks for underlying structures or hidden patterns in the input data. Typical tasks include association and clustering.

C. Reinforcement Learning

In this, the algorithm gains knowledge, through the interaction with the environment and feedback in the form of rewards or penalties. It is frequently utilized in gaming and robotics.

The algorithms used in machine learning are linear regression, decision trees, random forest, SVM, and neural networks.

III. PREDICTIVE MAINTENANCE

Predictive maintenance is largely dependent on software and technology, especially the combination of integrated systems, artificial intelligence, and the Internet of Things. By integrating diverse resources, these systems facilitate the exchange of data, analysis, and practical ideas. After that, this data is examined using methods including vibration analysis, thermal imaging, and equipment observation to identify areas that require care. WSN has always been an area of interest for researchers and real-time developers. Fig.1 shows the process of predictive maintenance.

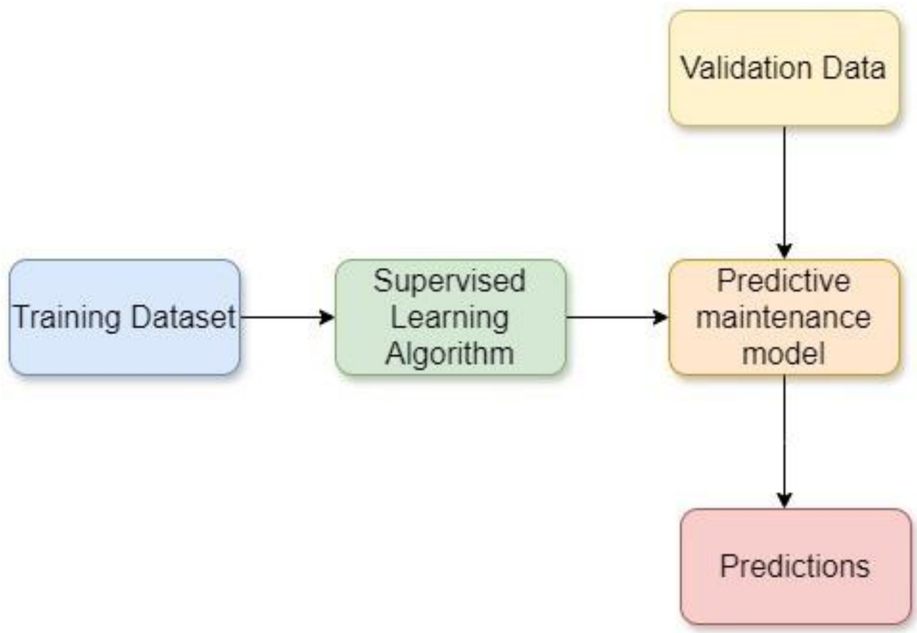

Fig. 1. Process of Predictive Maintenance

IV. TRAINING PREDICTIVE MAINTENANCE SYSTEM BASED ON MACHINE LEARNING

Predictive analytics and condition monitoring are the two subtasks that make up predictive maintenance. Therefore, developing a predictive maintenance solution basically consists of developing a detection model and incorporating it into a complete solution. In order to train these models, we must perform the following actions:

- Data Collection: Getting enough data to train the models is the first stage in developing a predictive maintenance method. Sensor data, failure data, operational data, environmental data, maintenance records, service reports, work orders, and other pertinent data are among the kinds of data that need to be gathered.
- Data Processing: Before creating a unique AI-driven predictive maintenance solution, data must be preprocessed. It uses a variety of methods, including handling missing numbers, eliminating outliers, and more. The features of your data will determine which processing methods are best, and understanding your hardware is essential to completing the task properly. Let's say you have data on noisy vibrations. Making the best preprocessing approach decision can be aided by understanding the frequency range containing failure markers.
- Feature engineering: It refers to the process of converting unprocessed data into characteristics that facilitate the differentiation between anomalous and typical behavior. To facilitate the identification of patterns and relationships by machine learning algorithms, the objective is to extract pertinent information from the data. Vibration data, for instance, can be used to track a gearbox's health. Vibrations can vary in frequency and intensity when a gearbox malfunctions. As a result, peak frequency and magnitude can be used to track gearbox health.
- Model Selection and Training: Using the collected data, the best machine learning model is then chosen and trained. Model selection: Choosing the right predictive model or machine learning algorithm is essential for the predictive maintenance use case. Several factors influence the choice of model, including as the nature of the data, the difficulty of the issue, and the desired degree of interpretability. Models vary in their advantages and disadvantages. Model Instruction: Training the machine learning predictive maintenance model with past data teaches it to recognize patterns and correlations between attributes and the target variable, such equipment failure. The two parts of the dataset are the training set and the testing set. The model can identify patterns in the data and predict outcomes as a result of learning from training data. After the model is trained, it is tested on the testing data set. Model validation is a crucial step to evaluate the predictive power of the model and ascertain how well it performs with unknown data.
- Integration and deployment: The model should be integrated into your system and used when it has been chosen, trained, and produced accurate predictions. Based on its specifications, you can deploy your machine learning predictive maintenance software in a variety of methods, such as cloud, edge, or hybrid.

V. LITERATURE REVIEW

WSN has been a valuable addition to the current wireless communication networks. The network lifetime of wireless sensor networks can be increased by choosing the best possible paths for data transfer because less energy is consumed. Numerous routings, power management, and data distribution protocols are created especially for wireless sensor networks, where energy awareness is a crucial design consideration. Since there is still no agreement on a standard communication stack for WSN, routing protocols in WSN may vary depending on the application and network architecture. To accommodate WSN, newer routing protocols are necessary [7].

The paper [8] discusses the various challenges which are required for the development of data-driven system for Predictive maintenance. The various challenges include collection, transmission and processing of large amounts of data, inaccurate and noisy sensor data and the equipment specific Predictive maintenance approaches. This paper provides different points of views which can offer solutions to these issues such as anomaly detection, elimination of noisy and inaccurate data.

The most current reviews of predictive maintenance-related literature and associated works are presented in this publication [9]. Additionally, a comparison and classification of the current methods are suggested. Research on predictive maintenance is still ongoing. Numerous issues were covered in several studies and surveys. A prevalent obstacle in the manufacturing sector is the absence of labelled failure data. Other challenges include managing uncertainty, designing and developing predictive maintenance systems without a systematic approach, ranging existing solutions to complex system applications with various components and related faults, combining large and different sources of condition monitoring data, incorporating external influence data. Three primary issues concerning Predictive maintenance are mentioned in this paper:

- Predictive maintenance system architectures should meet the fundamental needs of Predictive maintenance and should be easy to integrate with new future methods. They should also be compatible with a variety of industrial standards.
- Predictive maintenance goals should be carefully considered and determined in performance.
- Lastly, Methods for fault diagnostic and prognostication need to be created and customized.

In facilities where food and beverages are manufactured, predictive maintenance has become a game-changing method of equipment maintenance. Predictive maintenance (Predictive maintenance) enables food and beverage (F&B) firms realize major benefits, such as decreased downtime, increased product quality, optimized maintenance costs, greater safety, and longer asset lifespan, by proactively identifying and addressing probable equipment faults. Predictive maintenance can help food and beverage firms beat rivals by guaranteeing steady output, more flexibility, and a quicker reaction to shifting consumer demands. Through the optimization of energy consumption, reduction of water usage, and prevention of product deterioration, predictive maintenance can minimize wasteful use of resources. This is in line with the increasing demands for sustainable practices from consumers and regulations. The F&B industry's transition to a data-driven future is made possible by the implementation of Predictive maintenance. The information acquired can be applied to new ideas, process enhancements, and optimizations. By fostering a workplace that is more engaging and technologically savvy, Predictive maintenance can draw in and keep skilled workers. Lower consumer costs and better food security are the results of increased productivity and decreased waste, especially in areas with limited resources [10].

An extensive overview of Predictive maintenance system architectures, goals, and methodologies was provided in this study [11]. The authors started by giving a summary of the Predictive maintenance system architectures. They have presented the three categories of goals for completing Predictive maintenance tasks: numerous targets, availability/reliability maximization, and cost reduction. Next, the authors reviewed the current methods, which include knowledge-based, conventional ML-based, and DL-based methods. The focus is given to the deep learning-based methodologies that have generated academic curiosity over the years.

In this research, the authors developed a Predictive maintenance system for WSN using the FFNN machine learning model. They found that short M, small L, encoding, and quantization all increase system complexity. Using the raw (original data), small M, and large k improves accuracy. The authors plan to expand their methodology to encompass multi-hop WSN and apply it through additional machine and deep learning models [12].

It was observed during this review [13] that Predictive maintenance application design is gradually utilizing machine learning approaches. When Predictive maintenance and ML are integrated, there are instances where cost savings are realized. Nonetheless, it is evident that the combination of Predictive maintenance methods with cutting-edge sensor technology prevents needless equipment replacement, reduces expenses, and enhances process availability, efficiency, and safety. It should be noted that Predictive maintenance applications have effectively incorporated machine learning (ML) techniques as ANN, deep learning, and k-means. Nonetheless, there are still certain areas of Predictive maintenance and ML that require more research.

Case studies have shown that machine learning-powered predictive maintenance can greatly increase the lifespan of vital parts like gearboxes and bearings, improving wind turbine dependability and efficiency. Additionally, machine learning is essential for maximizing wind energy systems' efficiency. Due to the inherent variability of wind conditions, maintaining optimal turbine performance is difficult. Turbine settings can be dynamically adjusted depending on real-time data, credit is given to machine learning approaches like optimization algorithms and performance prediction models. This flexibility guarantees that turbines run as efficiently as possible, optimizing energy extraction and reducing losses. According to case studies, machine learning may enhance operational efficiency by accurately predicting power production, improve energy capture by optimizing blade pitch and yaw angles, and offer insightful information for improved turbine operation and design. When taken as a whole, these advantages improve wind energy's overall sustainability and competitiveness [14].

Significant production losses and higher maintenance expenses can result from unplanned outages in industry caused by machine malfunctions. Predictive maintenance techniques identify minor issues and avert significant breakdowns by using data gathered from IoT-enabled sensors put in operational machinery. In this [15] investigation, a predictive maintenance system based on machine learning algorithms—more especially, AdaBoost—is introduced to classify various machine stops in real time, with a knitting machine application. In order to classify six different types of machines stops—gate, feeder, needle, completed roll, idle, and Lycra—the machine learning model was provided pre-processed data from the machines, including machine speeds and steps. To reach a 92% accuracy rate on the test set, the model is trained and optimized with a combination of cross-validation and hyperparameter tuning techniques. The findings show how the suggested method could effectively categorize machine stops and facilitate prompt maintenance, increasing the textile industry's total productivity and efficiency.

Predictive maintenance has been made extremely difficult by the intricacy and risks of autonomous car systems. Regular maintenance should be carried out to ensure human safety because malfunctioning hardware and software in autonomous vehicle systems could result in fatal collisions. Large-scale product design for automotive systems depends heavily on anticipating future failures and adopting preventative measures to preserve system safety and dependability. In order to analyze the necessity for system maintenance in autonomous vehicles, this study will examine a number of machine learning algorithms, such as regression, classification, ensemble, clustering, and deep learning techniques. According to experimental findings, predictive maintenance can significantly benefit autonomous cars by enhancing system architecture or reducing the likelihood of hazards. Based on actual data, this paper describes two machine learning techniques for Predictive maintenance in AVs. One of the most crucial parts of the car, the high-voltage battery, has its SOH predicted by ML algorithms. The authors have introduced the first two ML-based Predictive maintenance algorithms that forecast the battery's state of health using actual AV data. In terms of accuracy and reaction time, the Stacked Autoencoder deep learning model has shown itself to be the most effective algorithm for the used dataset. With accuracy values that are comparable to the SLA values and a response time that is comparable to the SLA model, the second model—the Random Forest regressor—has also shown itself to be a decent model [16].

In order to help practitioners and non-expert users choose ML algorithms for Predictive maintenance problems, this paper [17] suggests a conceptual framework. The goal is to offer a set of standards and suggestions for determining which machine learning approaches are most likely to produce useful results for particular tasks or datasets. First, the key traits, benefits, and drawbacks of the most widely used machine learning algorithms in Predictive maintenance are examined. Following that, several decision factors are considered, including learning objectives, accuracy, interpretability, and dataset and machine learning features. Lastly, case studies that serve as examples are provided to show how the suggested framework might be used in actual industrial settings.

This comprehensive review [18] examines the evolving role of predictive maintenance within the Industry 4.0 framework. It highlights how predictive maintenance enhances manufacturing efficiency, reliability, and sustainability by leveraging data from advanced sensing technologies. The paper explores various predictive maintenance approaches, including Condition-Based Maintenance (CBM), Prognostics and Health Management (PHM), and Remaining Useful Life (RUL) estimation. Additionally, it addresses key challenges such as financial limitations, data quality issues, and the complexities of industrial implementation. The authors propose a structured workflow for integrating predictive maintenance strategies and introduce an innovative platform designed to support decision-making and data management in smart maintenance environments.

This study [19] highlights the immense potential of machine learning-based approaches in predictive maintenance for wireless sensor networks (WSNs), making a strong case for adopting advanced analytical techniques. The effective deployment of these algorithms not only supports industrial efficiency goals but also represents key progress toward realizing Industry 4.0 and IoT applications. The authors mention that the intersection of ML and Predictive maintenance in WSNs represents a significant advancement in the network management. Future research should focus on improving the real-time performance of these models, enhancing their interpretability, and investigating hybrid methodologies to foster more sustainable and efficient network management.

Paper [20] explores the advancement of predictive maintenance in industrial environments by integrating Machine Learning (ML) techniques with the Industrial Internet of Things (IIoT). The authors present a holistic approach that leverages multiple ML models, highlighting the significance of model selection for optimizing predictive maintenance. The research underscores IIoT's role in enabling real-time equipment monitoring, producing vast amounts of data essential for predictive analytics. It evaluates the effectiveness of ML models in forecasting equipment failures, offering a strategic framework to enhance maintenance practices, minimize operational downtime, and prolong the lifespan of industrial assets.

This study [21] mentions the fusion of data analytics and the Internet of Things (IoT) has revolutionized predictive maintenance in Industry 4.0, enabling businesses to adopt proactive strategies that enhance asset management and minimize unexpected downtimes. This review explores a range of data analytics techniques, from conventional statistical methods to advanced machine learning, underscoring their significance in predictive maintenance workflows such as real-time data acquisition, anomaly detection, and ML-driven analysis. The paper examines the interplay between IoT and data analytics in industrial settings, offering insights into their applications, benefits, and challenges in the shift toward smart manufacturing.

This paper [22] conducts a systematic literature review on predictive maintenance (Predictive maintenance) within the Industry 4.0 (I4.0) framework. It underscores the critical role of Predictive maintenance in improving the reliability and availability of production systems by leveraging advanced technologies such as AI, IoT, and big data analytics. The study provides an in-depth analysis of various AI-driven techniques used in Predictive maintenance, evaluating their advantages, limitations, and suitability for different applications. It highlights the necessity of customized strategies tailored to specific industrial settings and explores hybrid approaches that integrate multiple methodologies for enhanced predictive accuracy. The paper concludes by emphasizing the integration of Predictive maintenance with emerging technologies like digital twins and the need to address complex industrial systems for more effective maintenance strategies. Additionally, it stresses the importance of ongoing research in standardization, interoperability, and the continuous evolution of data analytics algorithms to further advance Predictive maintenance practices in the manufacturing sector.

In several industries, such as safety, mobility, the Internet of Things, and healthcare, wireless networks of sensors are growing in popularity. By improving comfort of life and social advancement while reducing ecological impact, these networks use smart sensors to support viable development. However, changes in network architecture and resource constraints make it difficult to guarantee Quality of Service (QoS). Enhancing factors like security, latency, and dependability is crucial to overcoming these obstacles. The paper [23] underlines the need of reliable paths and nodes in the transfer of data.

It explains a process in which cluster heads are chosen according to their connectivity to the base station, and nodes are distributed. Throughput and packet delivery ratio are two examples of QoS metrics that are calculated using the Ad Hoc On-Demand Distance Vector (AODV) architecture. Route and node ranks are evaluated by dividing the data into three categories (good, moderate, and bad) using a K-means clustering algorithm. To improve node ranking efficiency and overall network durability, the suggested model additionally incorporates statistical machine learning and swarm intelligence utilizing the dragonfly algorithm. Finally, it advocates merging deep learning with fuzzy logic to overcome issues in safe transmission of data and efficient route discovery.

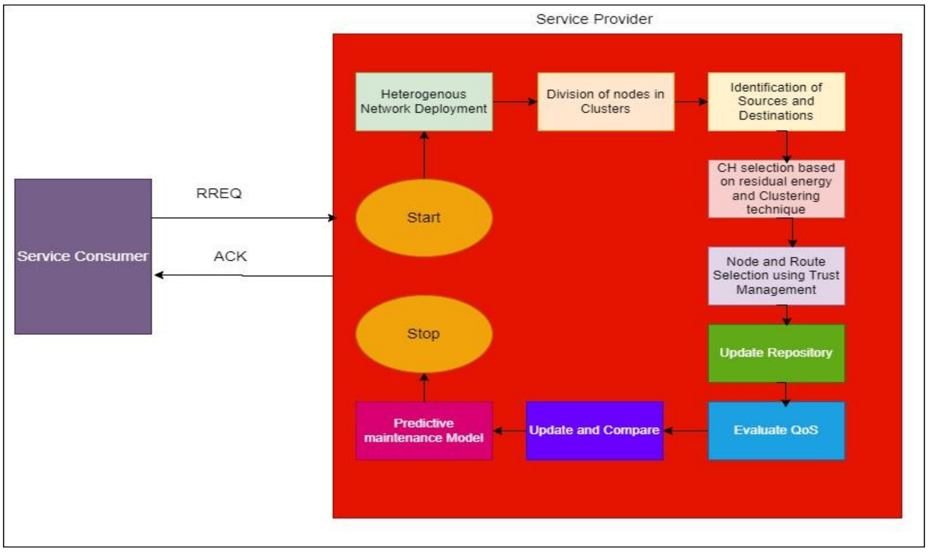

Fig. 2. Proposed Model of WSN employing Predictive maintenance

VI. CHALLENGES AND LIMITATIONS

Sensor data quality can affect predictive models' accuracy, and integrating data from various sources is complex. Predictive maintenance systems require significant investment, ongoing monitoring, and advanced statistical techniques. Skilled data scientists and engineers are needed, and employees need training. Scaling solutions across large enterprises can be challenging and resource-intensive.

Sometimes, predictive models might detect possible failures (false negatives) or generate false alarms (false positives), which can result in unplanned breakdowns or needless maintenance. Predictive models' accuracy and generalizability can be impacted by various equipment types and operational environments. Large-scale data collection and transmission can give rise to worries about cybersecurity and data privacy. Implementing predictive maintenance solutions that adhere to all relevant standards may be difficult for industries with stringent regulatory requirements.

Even with these difficulties, predictive maintenance frequently has more advantages than disadvantages, particularly as technology develops. Businesses that successfully handle these problems might benefit from increased operational efficiency lower expenses, and better dependability.

VII. FUTURE WORK

Sustainable networking is promoted by traffic prediction using anticipated repair learning and optimized route finding with the help of meta-heuristics. By anticipating patterns of energy use and preventing malfunctions, these blended approaches help increase the longevity of networks. Fig.2 shares the enhanced concept proposed in [23]. It is modified by adding the predictive maintenance model in the work proposed by the authors. With the help of this model, bad routes as well as nodes can be easily detected beforehand so that these can be ignored while sending the data. This results in real time predictive maintenance of the network. Using predictive maintenance model in extension to work done in [23], it advocates benefits of predictive maintenance in WSN based on machine learning to overcome issues in safe transmission of data and efficient route discovery. Hence the use of machine learning helps in reducing downtime and reducing energy consumption thereby increasing network lifetime and creating more intelligent and robust systems.

Further, wireless Sensor Networks (WSNs) are being revolutionized by federated learning, real-time predictive maintenance, and sophisticated machine learning models. Federated learning can be used to improve data privacy and to lower bandwidth consumption by enabling decentralized model training on edge devices. Utilizing real-time sensor data, real-time predictive maintenance minimizes downtime and maximizes resources by anticipating equipment faults. In WSNs, advanced machine learning models can be used to increase the precision of anomaly detection and predictive analytics, facilitating more effective network operations monitoring and management. When combined, these technologies improve the scalability, efficiency, and dependability of WSNs, spurring advancements in several sectors, such as manufacturing, healthcare, and smart cities.

VIII. CONCLUSION

In conclusion, there are several benefits to using machine learning for predictive maintenance in Wireless Sensor Networks (WSNs) in terms of improving operational dependability and efficiency. WSNs can precisely anticipate probable equipment breakdowns in real-time by employing sophisticated machine learning algorithms. This allows for preventive maintenance measures that reduce downtime and increase the lifespan of vital infrastructure. These capabilities are further improved by federated learning, which lowers communication overhead and protects data privacy. By incorporating these technologies into WSNs, maintenance schedules are optimized and innovation is stimulated in a variety of industries, leading to smarter and more robust systems.

This paper proposes a predictive maintenance model that forecasts the most effective routes and nodes via a feedback storage facility. The feedback repository serves as a support model for the ideal routes and points that can be relied on to ensure the transportation of data lacking any interruptions and energy waste. Predictive maintenance is an innovative idea that helps the system track and assess the present state of the platforms for which they are created. They also help to maintain the behavior of these networks by forecasting the future quality. The predictive maintenance in WSNs based on machine learning is a revolutionary method of preserving the functionality and health of intricate networks.

REFERENCES

[1] LK. Ketshabetswe , AM. Zungeru , M. Mangwala, JM. Chuma and B. Sigweni, "Communication protocols for wireless sensor networks: A survey and comparison", Heliyon. vol. 5, pp. 1-5, May 2019.

[2] MB. Ahmad, AA. Abdullahi, AS. Muhammad, YB. Saleh, and UB. Usman. "The Various Types of sensors used in the Security Alarm system." International Journal of New Computer Architectures and their Applications (IJNCAA), vol 9, no. 2, pp. 50-59, 2019.

[3] SA. El-Safty, MA. Shenashen. "Advanced nanoscale build-up sensors for daily life monitoring of diabetics". Advanced Materials Interfaces, vol.7 no.15, pp.2000153, 2020.

[4] YS. Can, B. Arnrich, C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: A survey", Journal of biomedical informatics, vol. 1;92, pp.103139, Apr 2019.

[5] OI. Uzougbo, SS. Ajibade, F. Taiwo. "An overview of wireless sensor network security attacks: mode of operation, severity and mitigation techniques". arXiv preprint arXiv:2011.06779. Nov 2020.

[6] D.Sethi, "An approach to optimize homogeneous and heterogeneous routing protocols in WSN using sink mobility". Mapan.vol.35(2), pp.241-50, 2020.

[7] AN. Shahbaz, H. Barati, A. Barati. "Multipath routing through the firefly algorithm and fuzzy logic in wireless sensor networks". Peer-to-Peer Networking and Applications, vol.14(2),pp. 541-58, Mar 2021.

[8] P. Nunes, J. Santos, E. Rocha. "Challenges in predictive maintenance–A review". CIRP Journal of Manufacturing Science and Technology, vol. 1;40, pp.53-67, Feb 2023.

[9] H. Meriem, H. Nora, O. Samir. "Predictive maintenance for smart industrial systems: A roadmap". Procedia Computer Science. Vol.220, pp.645-50, Jan 2023.

[10] DO. Uzoigwe. "Implementing predictive maintenance (Predictive maintenance) programs in food and beverage manufacturing facilities". International Journal of Research and Innovation in Applied Science.vol. 8(12),pp.103-18, 2023.

[11] T. Zhu, Y. Ran, X. Zhou, Y. Wen. "A survey of predictive maintenance: Systems, purposes and approaches". arXiv preprint arXiv:1912.07383. Dec 2019 .

[12] M. Almazaideh, J. Levendovszky. "A predictive maintenance system for wireless sensor networks: a machine learning approach". Indonesian Journal of Electrical Engineering and Computer Science.Vol.25(2), pp.1047-58, Feb 2022.

[13] TP. Carvalho, FA. Soares, R. Vita, RD. Francisco, JP. Basto, SG. Alcalá. "A systematic literature review of machine learning methods applied to predictive maintenance". Computers & Industrial Engineering.vol.137,pp.106024, Nov 2019.

[14] WS. Udo, JM. Kwakye, DE. Ekechukwu, OB. Ogundipe. "Optimizing wind energy systems using machine learning for predictive maintenance and efficiency enhancement". Journal of Renewable Energy Technology. vol.28(3), pp.312-30, 2024.

[15] S. Elkateb, A. Métwalli, A. Shendy, AE. Abu-Elanien. "Machine learning and IoT–Based predictive maintenance approach for industrial applications". Alexandria Engineering Journal, vol.88, pp.298-309, Feb 2024.

[16] CV. Shah. "Machine learning algorithms for predictive maintenance in autonomous vehicles". International journal of engineering and computer science, vol.13(01),pp.26015-32, Jan 2024.

[17] S. Arena, E. Florian, F. Sgarbossa, E. Sølvsberg, I. Zennaro. "A conceptual framework for machine learning algorithm selection for predictive maintenance". Engineering Applications of Artificial Intelligence. Vol.133, pp.108340, Jul 2024.

[18] M. Achouch, M. Dimitrova, K. Ziane, S. Sattarpanah Karganroudi, R. Dhouib, H. Ibrahim, M. Adda. "On predictive maintenance in industry 4.0: Overview, models, and challenges". Applied Sciences.vol.12(16), pp.8081, Aug 2022.

[19] M. Salman. "Machine Learning Algorithms for Predictive Maintenance in Wireless Sensor Networks". International Journal of Sciences and Innovation Engineering.vol.1(1), pp.1-8, Sep 2024.

[20] SO. Alhuqayl, AT. Alenazi, HA. Alabduljabbar, MA. Haq. "Improving Predictive Maintenance in Industrial Environments via IIoT and Machine Learning". International Journal of Advanced Computer Science & Applications.vol.15(4), Apr 2024.

[21] M. Soori, FK. Jough, R. Dastres, B. Arezoo. "Blockchains for industrial Internet of Things in sustainable supply chain management of industry 4.0, a review". Sustainable Manufacturing and Service Economics. vol 11, pp.100026, Jul 2024.

[22] FM. Abdelillah , H. Nora , O. Samir , SM. Benslimane . "Predictive maintenance approaches in Industry 4.0: a systematic literature review". IEEE International Conference on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE) vol.14, pp. 1-6, Dec 2023.

[23] S. Sharma, A. Kaur, D.Gupta, S. Juneja, M. Kumar. "Dragon fly algorithm based approach for escalating the security among the nodes in wireless sensor network based system". SN Applied Sciences.vol. 5(12), pp.376, Dec 2023.