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Advanced AI-Powered Energy Optimization Strategy for Industrial Wireless Sensor Networks.

Neelakanth Jadhav[1], Varsha J. Rathod[2]
[1,2] Lecturer Electronics and Communication Engineering

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ABSTRACT

The capacity of Wireless Sensor Networks (WSNs) to gather and transmit data from the physical world has drawn a lot of interest in a variety of fields. Intelligent decision-making and the extraction of valuable insights from the acquired data have become possible thanks to the integration of machine learning techniques into WSNs. The applications of machine learning in WSNs are thoroughly reviewed in this research, which also addresses the difficulties in putting them into practice. We emphasize the many uses of machine learning techniques in WSNs and discuss the main obstacles and constraints that researchers have faced in our review of the state-of-the-art research in this area. We also talk about possible future paths for utilizing machine learning in WSNs to improve their capabilities and tackle new issues. The purpose of this study is to serve as a useful guide for scholars and professionals who are curious in the uses, difficulties, and potential of machine learning in WSNs.

52.16% idle-mode energy consumption, 47.84% idle-mode energy storage, 66.31% sleep mode energy consumption, 33.69% sleep mode energy storage, 64.72% transmission energy use, 35.28% transmission energy saving, 67.27% received energy consumption, and 32.73% received energy storage were all achieved by the proposed EEOM. Additionally, its prevalence threshold, critical success index, Delta-P, MCC, and FMI rates were 90.44%, 90.33%, 93.93%, and 94.20%, respectively. Additionally, it has the capability to determine the optimal node and choice of path for data transfer to minimize network traffic. Industrial WSNs will become more dependable, efficient, and energy-efficient when these automated knowledge-based procedures are used in conjunction with manual intervention [16].

Keywords: *Wireless Sensor Network, Data, Machine Learning, Research, Industrial, Scalability, Performance*

I. INTRODUCTION

Specialized wireless networks used in industrial contexts, including industrial automation, process control, monitoring, and safety, are known as industrial wireless sensor networks, or IWSNs [1]. A group of sensor nodes placed throughout a region of interest for monitoring purposes makes up an IWSN [2]. To transmit data to a supervisory agent or control application, they are wirelessly connected to a base station and gateway node. Sensors, transceivers, microcontrollers, and power supply make up sensor nodes, which frequently use a variety of wireless protocols to maximize their performance and power usage [3].

Wireless Sensor Networks (WSNs) are a potent technology that makes it possible to monitor physical environments intelligently and widely. Small, energy-constrained sensor nodes work together to gather, process, and send data in these networks. WSNs are used in many different fields, including industrial automation, smart cities, healthcare, agriculture, and environmental monitoring. However, conventional data processing methods face major obstacles due to the enormous volumes of data produced by WSNs [4]. The development of clever and effective data processing techniques is required due to the complexity and scale of WSNs, resource constraints, and changing environmental circumstances. Machine learning, a branch of artificial intelligence, can be extremely helpful in this situation. Without explicit programming, machine learning algorithms may automatically identify patterns in data and use that information to create predictions or judgments. We can open new possibilities for data-driven decision-making, adaptive behavior, and resource optimization by utilizing machine learning in WSNs.

1.1: MOTIVATION

The growing need to utilize machine learning capabilities in WSNs is what inspired this research work. Conventional methods for processing data in WSNs frequently depend on manual rule-based algorithms or oversimplified models that might not fully utilize the wealth of information present in the data. By allowing WSNs to learn from the past, adjust to changing settings, and derive insightful information from the gathered data, machine learning presents a possible option. Several facets of network functioning could be enhanced by incorporating machine learning into WSNs. Among other things, it can improve energy management, data fusion, anomaly detection, localization, fault diagnostics, and security [3]. WSNs can increase their accuracy, energy economy, scalability, and adaptability by utilizing machine learning techniques, which allows them to grow.

1.2: OBJECTIVES

Enhanced Productivity: Industrial wireless sensor networks can precisely monitor and analyze data to spot possible problems and provide fresh, more effective methods to boost production efficiency thanks to machine learning algorithms.

Predictive Maintenance: Machine learning algorithms can anticipate when maintenance is required and identify irregularities in the data gathered from industrial wireless sensor networks. It lowers the expenses and downtime related to unforeseen repairs.

Improve Safety: Algorithms that use machine learning can identify possible risks in operating settings and notify operators to take preventative action.

Automation: Industrial wireless sensor networks can increase accuracy and lower labor costs by automating operations and processes [1].

Improve Quality: By detecting and identifying product flaws prior to shipment, machine learning algorithms can save return costs and boost customer satisfaction.

By tackling these goals, this study intends to advance knowledge, advancement, and implementation of machine learning methods in wireless sensor networks, opening the door for data-driven, intelligent, and autonomous WSN applications.

II. LITERATURE REVIEW

The effectiveness of industrial wireless sensor networks (WSNs) has long been a major topic of engineering research and development, as ***Ramesh et al. [20]*** have discussed. The reason for this is that WSNs are frequently employed in industrial settings for automation and remote monitoring. The demand for proper energy optimization of WSNs is growing along with the number of these networks used in different industrial applications. Energy optimization is acknowledged to be necessary for WSNs to maintain optimal communication performance and guarantee effective operation.

Advanced energy optimization models, including the Energy Efficient Optimization (EEO) model created for industrial WSNs, have been covered by ***Ahmad et al.*** [13]. The foundation of the EEO model is the idea that node energy levels may be predicted using machine learning methods, enabling more precise energy use. Using dynamic resource-allocation strategy adjustments and predictive optimization approaches, the EEO can improve the energy optimization of industrial WSNs. According to ***Shanmugasundaram and Madheswaran et al.*** [18], there are multiple approaches to achieving energy optimization in industrial wireless sensor networks using the EEO model [3].

First, machine learning approaches can be used to suggest algorithms that accurately estimate the energy levels of the nodes. It will enable the network to lower overall energy usage and more effectively distribute resources to nodes with higher amounts of leftover energy. ***Matlou and Abu-Mahfouzetal*** [15] have talked about using machine learning techniques to monitor energy levels throughout the network and have pinpointed regions that need improvement so they may be more effectively targeted. A dynamic policy switch feature in the EEO allows resource-allocation techniques to be modified for various network conditions. This feature allows the resource-allocation policy to be tailored to the state of the network at any given time.

Additionally, this technology minimizes energy usage by enabling a quick response when network circumstances change. WSN routing behavior can be managed with the EEO. The EEO can precisely identify and optimize the routing paths when used with machine learning, which improves energy efficiency and data routing. The enhanced energy optimization model, which is based on machine learning and can aid in improving the energy optimization of industrial WSNs, has been used in discussions by ***Praveen et al.*** [16]. The EEO can offer a more effective method of energy optimization by enabling dynamic resource allocation strategies and predicting node energy levels using machine learning algorithms.

Energy efficiency can also be enhanced by employing this model to regulate the data routing process. According to ***Yang et al.*** [17], wireless sensor networks (WSNs) are being utilized more and more in contemporary industrial settings to enable precise and effective control and monitoring of intricate systems and processes. The accuracy, efficiency, and dependability of the networks can be further improved by implementing different optimization techniques. WSN energy optimization has been covered by ***Blake et al.*** [18] as a tactic that aims to reduce energy usage while enhancing network performance.

Galbraith and Podhorska et al. [19] have talked about using supervised learning to optimize energy consumption in IWSNs. This method can be used to improve energy usage by using machine learning (ML) methods, such as artificial neural networks and decision trees, to detect possible problem areas, such as imbalanced node load and nodes' received signal strength (RSS). Results from experiments and simulations are used to assess the suggested plan. A real-world IWSN deployment was used in studies conducted indoors by ***Matusowsky et al.*** [13]. According to the simulation results, the suggested strategy can successfully lower IWSN energy usage. The results demonstrate that, in a variety of radio channel situations, the suggested model can dramatically lower the network's energy usage. Pinto and associates.

III. PROPOSED SYSTEM

The need for more effective energy models is rising as our energy and economic systems become more intertwined. The necessity for industrial wireless sensor networks has grown as a result. These networks make it possible to collect and analyze data using machine learning algorithms in real time and with accuracy. Figure 1 below depicts the structure of an industrial wireless sensor network.

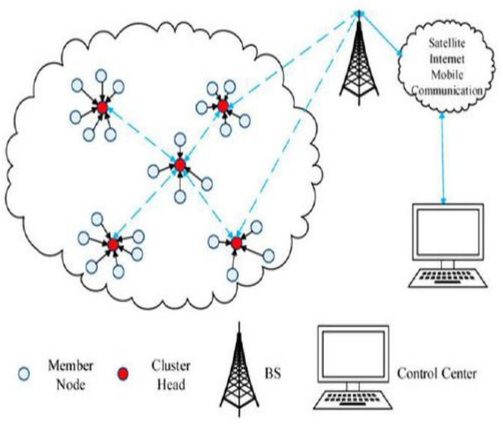

Figure No.1: Structure of an industrial wireless Network

The energy system's efficiency can be maximized with the aid of this technology. There are numerous advantages to putting an effective model into practice. By modifying the network parameters in real-time in response to feedback, it can first lower the energy cost. Second, it can improve the precision of the data collected by the sensors, enabling more precise trend analysis and forecasting. Lastly, by keeping an eye on the surroundings and warning the user of any changes that might pose a safety risk, it can improve environmental safety and security. A machine learning method and an energy management layer make up the energy optimization model. Data from several sensors across the network can be gathered and stored by the energy management layer. Additionally, it enables data preparation for analysis and control parameter adjustments based on observed data [11]. To maximize the efficiency of the energy system, the machine learning algorithm analyzes the collected data, generates forecasts, and offers suggestions. The development of algorithms that allow the system to precisely forecast energy use and select the best management parameters for optimal energy savings is crucial to ensuring that this model is successful in boosting energy efficiency. These algorithms also need to take into consideration the many kinds of data, devices, and interactions that occur in the environment. Enough hardware, software, and network resources will be needed for this model's implementation to adequately monitor and analyze the data.

IV. METHODOLOGY

To design the network, create the software, and set up the hardware, an experienced team is necessary. Operators and staff should also have the proper training so they can comprehend the system and how it works. The efficiency of industrial sites around the world can be significantly increased by putting an effective model into practice. This technology can lower expenses, save energy, and enhance security and safety. Therefore, it merits more investigation as a potential remedy for industrial locations. This model is a brand-new, potent technology that improves the robustness and efficiency of communication between several nodes. Intelligent digital networks for a range of industrial uses, including digital device control, industrial automation, and monitoring, can be created with this technology [10].

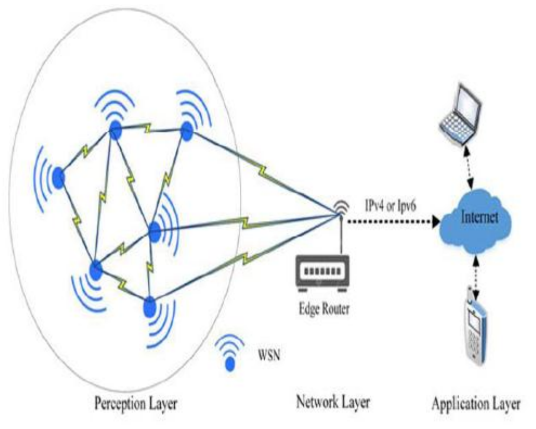

Figure No. 2: Layer Configuration

Layer arrangement as depicted in Figure 2. The integrated solar nodes that make up these networks are outfitted with hardware and software that facilitates data gathering and communication with other network nodes. The system is powered by solar energy, which is also used by solar nodes to transmit data over the network. The machine learning algorithms are built into the nodes then read, gather, and store this data. Reducing the quantity of messages transmitted across sensor networks and increasing the accuracy of the data sent are two ways that machine learning algorithms can increase communication efficiency. Moreover, trends in the data can be found using machine learning, which speeds up data classification and network security threat detection [19].

Increasing Efficiency: By lowering overall energy expenditures and working toward higher sustainability, an energy optimization model's main objective should be to maximize energy efficiency. Alternative energy sources, energy-efficient appliances, and LED lighting are a few strategies that should be considered. Minimizing Energy Waste: Any energy produced or used should be used sensibly and effectively, according to an energy optimization model. It entails evaluating present usage trends, spotting possible waste or inefficiencies, and using tools like timers, sensors, and remote monitoring to help guarantee energy is being utilized effectively [9].

Improving User Comfort: A model for energy optimization should aim to achieve the ideal balance between cost reduction and comfort. For instance, lowering thermostats to save energy may save money, but if the temperature drops too much, it may also make users less comfortable. Energy-efficient equipment purchases, and insulation are two strategies that should reduce costs while increasing customer happiness. Resource Conservation: Since resources are getting harder to come by an energy optimization model should also aim to use less resources overall. It can entail recycling current materials and equipment, implementing energy-saving and cutting-edge monitoring technology, and increasing efficiency using renewable energy sources [6].

V. ALGORITHM

An enhanced decentralized method of communication serves as the foundation for the suggested paradigm. The nodes are arranged in clusters, and a secure environment is used for inter-node communication. Using machine learning methods, the clusters in this edition of the improved energy optimization model for industrial wireless sensor networks can recognize unusual communication patterns and possible flag dangers. It makes the connections between the nodes more secure, which can assist safeguard the information sent over the network. With the help of the suggested paradigm, numerous nodes can communicate more accurately, securely, and efficiently. The functions of the suggested model are displayed in algorithms [4].

Algorithm 1 Enhanced energy optimization algorithm

1. Start
2. Compute the node 'i' and $F_{CH-Value}$
3. Generate random value between 0 and 1
4. If ($F_{CH-Value} > K$)
5. Then node 'i' can competes with other CHV nodes
6. the Node 'i' is non CHV
7. If the node 'i' is the winner
8. Then Node 'i' is CHV
9. Else go to step 6
10. End

In the long term, this technology can assist wireless sensor networks become more economical and efficient by increasing their energy efficiency. The suggested model is a cutting-edge approach made to lower wireless sensor networks' energy usage. The suggested model's flow chart is displayed in Fig. 3 below.

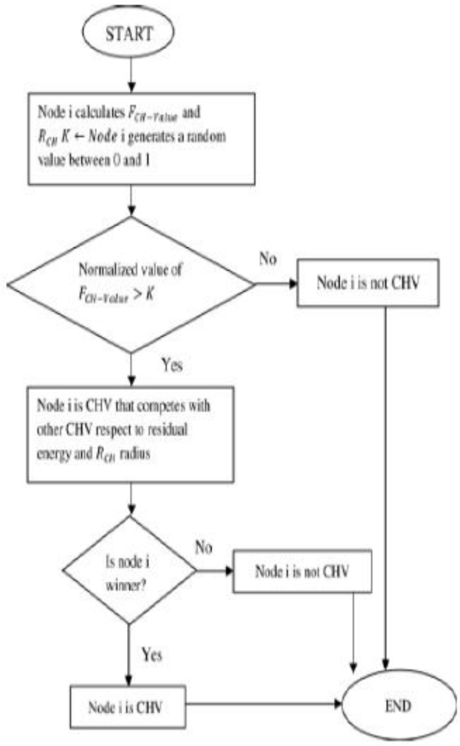

Figure No. 3: Flow Diagram of Model

This model more efficiently optimizes energy use by fusing two state-of-the-art technologies: wireless sensors and machine learning.

Predictive analytics serves as the foundation for the increased energy optimization model's operation. It predicts how much energy will be needed for the intended operation by using machine learning techniques to find trends in the energy consumption of wireless sensors. It guarantees that the energy utilized is minimized and optimized for the task. Several procedures and methods are employed to guarantee that the model is successful and efficient in lowering energy usage. To determine and forecast the energy requirements in regions with greater sensor concentrations, the model makes use of clustering and pattern recognition techniques. It enables the model to precisely forecast the energy needed for these clusters to function. Furthermore, the model employs adaptive strategies to modify the wireless sensors' power consumption in response to shifting environmental demands and conditions. It permits improved energy optimization and guarantees that energy consumption is optimized even when external conditions and demands alter. Additionally, the model employs reinforcement learning to grow from its errors and modify to maximize energy consumption while in operation. It allows the model to optimize energy consumption by modifying its energy settings according to the tasks and conditions [10].

VI. IMPLEMENTATION AND RESULT

The suggested model effectively powers the sensors in industrial settings by utilizing cutting-edge machine learning approaches. To maximize energy usage and guarantee a continuous flow of data from the sensor nodes in an industrial network, this sophisticated model that makes use of machine learning techniques provides a revolutionary power optimization methodology. The sensors can be controlled independently to reduce energy consumption and satisfy the system requirements of the application. By lowering the power needs of each sensor on an industrial network, this model also makes better performance possible. The way the model operates is by optimizing each sensor's transmission settings within a network or cluster of networks. It employs several strategies to appropriately set up each sensor while considering its energy properties. The model then calculates the ideal transmission parameters for every sensor using complex algorithms. Determine whether the communication node possesses both the transmitted energy (t) and the received energy (r). Next, it has the channel matrix "m" with the Gaussian noise additive (n) given in equation 1.

$$r = (m * t) + n$$

Equation 2 is now used to calculate the output of the network's first sensor node in the first cluster.

$$S_a^f = t_a * \left(\sum_{p=1}^{n} W_{1p} * t_p + \beta_p \right)$$

To minimize energy usage while still satisfying the requirements of the network and application, the model also makes use of machine learning techniques to optimize the settings of each sensor in the network. The improved energy optimization model can swiftly adapt and modify its characteristics in response to changes in the environment and the condition of the sensor nodes. By researching the machine learning techniques employed in the model, the increased energy optimization model's performance can be further enhanced. One may make sure the model generates the best result by being aware of the limits of these approaches. Furthermore, the model can be adjusted for environments, like an industrial setting [12].

Deep learning-based physical layer (DLBPL), Deep Learning-Assisted Smart Process Planning (DLASP), energy-efficient algorithm (EEA), and outlier detection in wireless sensor networks (ODWSN) have all been compared to the performance of the suggested enhanced energy optimization model (EEOM). In this case, the instrument utilized to carry out the results is the network simulator (NS-2). For comparison, the industrial wireless sensor networks dataset [39] has been used. For the analysis, 7846 samples in total have been collected. Thirty percent (2354 samples) were used for testing, and seventy percent (5492 samples) were used for training. The simulation parameters are displayed in Table 2.

PARAMETER	VALUE
Estimated simulation Area	1150m×1150m
SIFS (Short Inter-Frame Space)	35 sec
DR_T (Data Rate for Transmission)	240 kbps
IDR (Interference detection rate)	70 ms
T_P (Primary slot time)	15 ms
B_S (Bandwidth for Sub-channel)	220 MHz
B_C (Bandwidth for Channel)	120 MHz
F_C (Carrier frequency)	32.46 MHz
T_S (Simulation duration)	2 min (120 sec)

Table 1: Simulation Analysis

In industrial wireless sensor networks (IWSNs), machine learning has significant potential to lower transmit energy usage. First, patterns in the data gathered from the sensors can be found using machine learning. Machine learning algorithms can identify irregularities and inefficiencies in the system and recommend adjustments that can lower energy use by evaluating the data. The suggested technique can determine when a sensor can be turned off until the data is required or when it is delivering redundant or unneeded data [18].

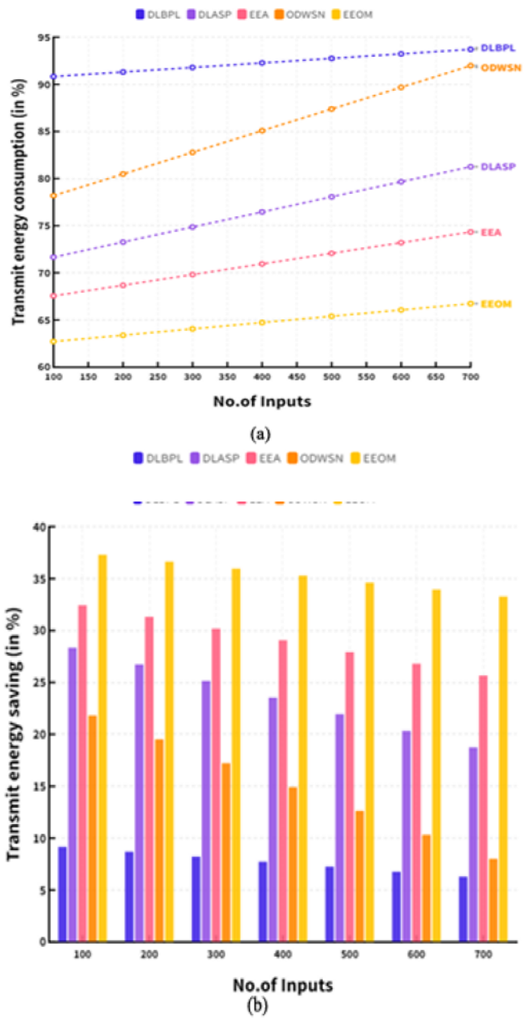

Figure No. 4 : (a) Estimation of transmit energy consumption. (b) Estimation of transmit energy saving.

The assessment of transmitting energy between the suggested and current models is displayed in Fig. 4. Figure 4. (a) Shows the energy usage of the transmission, and Fig. 4. (b) Stands for energy conservation through transmission. By optimizing the transmission power, the suggested algorithm aims to lower the energy consumption of the sensor nodes. The suggested method can be used for IWSN transmission scheduling. The network can reduce its energy consumption by scheduling transmissions during the most advantageous times by forecasting when each node will broadcast. The calculation of transmit energy consumption between the suggested and current models is displayed in Table. Based on the information it gathers from the surroundings; the model uses machine learning algorithms to determine each node's optimal transmission power. The energy needed can be decreased by using the machine learning algorithm to identify trends in the data and modify the transmission power appropriately. Up to 40% less energy can be used by the network with the aid of this approach.

Based on the findings of the experiments and theoretical work, the project will be completed by creating an efficient energy optimization model for industrial wireless sensor networks. The model will be used as a guide for designing and running industrial wireless systems, both current and future. The entire performance comparison is displayed in Table 1. The total energy usage and savings are displayed in Table 1. It is anticipated that using the suggested energy optimization methodology will increase industrial wireless networks' energy efficiency and help create a more sustainable energy sector. The estimation of overall performance between the suggested and current models displayed in Figure 4 shows the amount of energy used, and Figure 4 shows the amount of energy saved. The comparison of overall performance is shown in the proposed EEOM achieved 64.72% transmission energy consumption, 35.28% transmission energy saving, 67.27% received energy consumption, 32.73% received energy storage, 52.16% idle-mode energy consumption, 47.84% idle-mode energy storage, 66.31% sleep-mode energy consumption, and 33.69% sleep-mode energy storage, as a point of comparison [13].

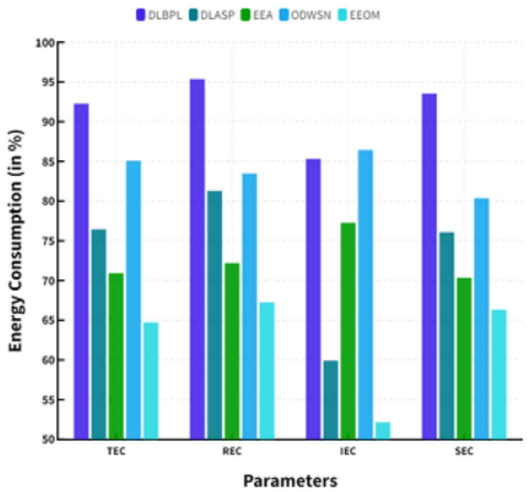

Figure No. 5 – Parameter

the energy networks' security since it adds another level of encryption. Energy networks can become safer and more resilient against all types of cyber threats by utilizing blockchain technology [7].

VII. CONCLUSION

Enhancing industrial wireless sensor networks is possible with the aid of the EEOM. To maximize the integration of sensor data into industrial operations, the EEOM makes use of machine learning (ML). It makes process and data management interactive, extremely accurate, and effective. The costs of setting up, maintaining, and running industrial wireless sensor networks can be decreased by using the EEOM to construct these networks with high accuracy and low energy consumption. The EEOM ML model processes data from sensors and other network nodes using evolutionary techniques. In order to maximize energy efficiency and improve accuracy, this procedure controls the power of individual sensors, nodes, and subnets. 52.16% idle-mode energy consumption, 47.84% idle-mode energy storage, 66.31% sleep-mode energy consumption, 33.69% sleep-mode energy storage, 67.27% received energy consumption, 32.73% received energy storage, and 64.72% transmission energy consumption and 35.28% energy saving were all achieved by the proposed EEOM. Additionally, it achieved rates of 90.44% for the prevalence threshold, 90.33% for the key success index, 93.93% for Delta-P, 90.06% for MCC, and 92.17% for FMI. To guarantee the most effective operation, it can also consider various energy sources, such wind and sunshine. By incorporating the potential locations of individual nodes into its computations, the model can produce more accurate results.

To supervise the functioning of the complete industrial data management system, the EEOM ML model also incorporates a centralized control unit. It reduces the quantity of erroneous reading and guarantees optimal accuracy. The EEOM model effectively learns from mistakes and determines the optimal settings for every network node by utilizing machine learning capabilities. For wireless sensor networks in industry, the EEOM paradigm is quite helpful. Optimizing the process of gathering and managing data can result in significant cost savings. Additionally, the parameters can be adjusted to the circumstances to get the best results by using machine learning (ML) to enhance network operation. Manufacturers and industrial operators can save costs and maintain high accuracy by using the EEOM model.

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