

ORIGINAL ARTICLE

A novel energy optimization framework to enhance the performance of sensor nodes in Industry 4.0

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Abstract

Industry 4.0 is a term used to refer to the fourth industrial revolution, characterized by the introduction of new technologies, such as the Internet of Things, Big Data, and artificial intelligence (AI). As the number of connected devices in industrial settings grows, energy optimization of such sensors becomes increasingly essential. This paper proposes an energy optimization framework for sensor nodes in Industry 4.0. The framework is based on energy efficiency, energy conservation, and energy harvesting principles. It is designed to optimize the energy consumption of sensor nodes while maintaining their performance. The framework includes dynamic power management, scheduling, and harvesting techniques to reduce energy consumption while maintaining performance. In addition, the framework provides a comprehensive approach to energy optimization, including advanced analytics and AI to predict energy consumption and optimize energy use. The proposed model reached 96.93% sensitivity, 91.36% false discovery rate, 11.28% false omission rate, 90.12% prevalence threshold, and 91.24% threat score. The proposed framework is expected to improve the performance of sensor nodes in Industry 4.0, enabling increased efficiency and cost savings.

KEYWORDS

artificial intelligence, energy scheduling, big data, IoT, Industry 4.0

1 | INTRODUCTION

A wireless sensor network (WSN) is an integrated system of nodes connected to collect data over a wide area. It enables distributed sensing, measurement, and communication capabilities in dynamic environments.¹ In Industry 4.0, WSNs are essential for collecting, transmitting, and analyzing the large amount of data generated by

Internet of Things (IoT) devices and distributed systems. These networks use low-cost, low-power radio frequency (RF) communication to quickly collect data from a variety of sensors located throughout a larger area, such as temperature, light, pressure, and noise sensors.² This data can then be transmitted to a central processing hub for further aggregated analysis or real-time applications. WSNs are also used in predictive maintenance operations

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where data can be collected from condition-monitoring sensors to predict failures and other occurrences.³ As WSNs are low-cost to deploy and maintain, they are becoming increasingly popular in Industry 4.0 environments as a way to create smart and connected factories and plants. A sensor node, also known as a mote, is a small computing device that acts as a bridge between a physical environment and a cloud-based, data-driven computing system.⁴ In Industry 4.0, sensor nodes are used to collect data from machines, objects, and people, enabling the efficient operation of industrial systems.⁵ The nodes can be used to detect and collect a wide variety of inputs, such as temperature, pressure, vibration, motion, location, sound, and light. This data is communicated to a gateway or host computer, which then transmits the data to a cloud-based server for further analysis.⁶ By combining sensor nodes with artificial intelligence (AI) capabilities, systems can enable predictive and proactive maintenance, as well as optimized production. Sensor nodes in Industry 4.0 experience several communication issues that can affect the overall functioning of a network.⁷ These issues include limited radio range, interference from other networks, unreliable bandwidth, energy consumption, and cost of deployments. These issues are more likely to occur due to several factors, such as the high density of sensor nodes in a given area, lack of proper communication protocols and standards, data security and privacy, latency, scalability, and hardware constraints.^{8,9} Sensor nodes are essential for Industry 4.0 to collect and exchange data between machines to automate production. However, they present several energy issues.¹⁰ Each device requires energy to store and transmit the sensors' data, and long-term operation requires a reliable energy source. Power sources such as solar panels and batteries are used to alleviate power strain. Still, both are affected by external conditions, such as weather and relative humidity, which limits their effectiveness. Sensors often require considerable energy to transmit data, which produces significant power demands.¹¹ To avoid energy loss due to leaking, incorporating energy harvesting techniques, such as kinetic and thermal energy scavenging, is essential for optimizing sensor node battery life. Furthermore, energy conservation strategies such as power-saving protocols must be used to manage energy consumption.¹²

1.1 | Node level optimization

Node-level optimization is the configuration of individual sensors so that they are optimally configured to fulfill certain tasks. This optimization of individual sensors allows for faster, more consistent data collection, as well

as greater efficiency in using resources.¹³ In Industry 4.0, sensor nodes are essential for collecting data from the physical environment, and sensor node level optimization ensures that the data collected is accurate and up to date. For example, the number of sensors used could be reduced in certain parts of the factory where the sensors do not need to observe as much activity. It would reduce the energy and resources required for data collection from those areas while still providing the same level of accuracy and timely updates.¹⁴

Idle mode sensor nodes: Sensor nodes in Industry 4.0 are the backbone of the connected factory. They allow machines to communicate with one another and with the cloud to coordinate their actions and optimize the entire production environment. In idle mode, sensor nodes perform measurements, such as temperature, pressure, vibrations, and other environmental parameters, without requiring direct involvement from the humans operating the production line.¹⁵ It helps to provide an early warning of any unexpected conditions on the factory floor, allowing the factory's AI to take proactive action to resolve any issues. Additionally, sensor nodes in idle mode also provide valuable data for predictive analytics, helping to anticipate anything that might disrupt production.¹⁶ Sensor nodes for idle mode in Industry 4.0 can suffer from performance issues due to a variety of factors, including low power consumption, limited communication range, limited memory, and unreliable connections.¹⁷ Low power consumption can result in sensor nodes running out of energy quickly when not in active use, and limited communication range can reduce the effectiveness of the lifeless nodes in processing and receiving data. Limited memory can cause inefficiencies in data management, leading to the need to reprogram or clear nodes regularly. Finally, unreliable connections can also cause problems since data sent to the idle sensor nodes may never be received.¹⁸

Sleep mode sensor nodes: Sensor nodes operating in sleep mode can be an extremely effective way of reducing energy consumption and increasing efficiency in Industry 4.0. Sleep mode allows the sensor node to shut down activities, such as data processing and communication, and remain in a state of low power consumption.¹⁹ It has many benefits for IoT-enabled industrial environments, including reducing overall power consumption, increasing the lifespan of the sensor nodes, and providing better reliability to the overall system. In addition, sensor nodes using sleep mode can remain dormant until an external event, such as an increase in temperature or humidity or a change in the production line, triggers them. It allows the nodes to remain idle until the changing conditions dictate a response.²⁰ Sleep mode also helps to ensure that the sensor nodes are not needlessly drawing power from

the grid and consuming resources, which leads to cost savings. Lastly, sleep mode also helps to provide better scalability for IoT-enabled environments, enabling the addition of more sensor nodes with minimal changes to the existing system. One of the most common performance issues of sensor nodes in Industry 4.0 is the power consumption in sleep mode. Many sensor nodes are powered externally and need to be kept awake for a specified period to be able to send periodic information.²¹ If the sleep mode is not programmed correctly, it can cause the power consumption to be too high, resulting in insufficient battery life. It can have a detrimental effect on the cost-effectiveness of the IoT system in the long term. Additionally, if the sleep mode is not configured to reduce power consumption correctly, it can reduce the accuracy of sensor readings, causing the system to make incorrect decisions.²²

Active mode sensor nodes: Sensor nodes in industrial networks play a critical role in Industry 4.0, as they provide the necessary input and output into the automation process. In an active mode, sensor nodes are used to actively measure and collect data from various sources, including physical processes, environmental sensors, and others.²³ This collected data can be used to optimize and automate the process, provide insights into operations, and aid in predictive maintenance. In addition, the collected data can be used to trigger alarms in the event of any abnormal activity. Sensor nodes in an active mode, therefore, provide a more accurate and timely representation of the situation in the industrial process. The performance issues of sensor nodes for active mode in Industry 4.0 are mainly related to the size and complexity of the networks that comprise them. As the range of applications continues to grow, so too does the number of nodes within a network. It reduces the average bandwidth available to the nodes as more of the available bandwidth is taken up by traffic related to the increasing number of nodes.²⁴ In addition, the more complex the network becomes, the more complex and energy-consuming devices the sensor nodes need to be to meet the demands of the application. It can reduce the device's battery life, shortening its lifespan. Finally, some nodes might need to be positioned closer to the gateway for the signals to travel, which can reduce the reliability of the connection.²⁵

1.2 | Network level optimization

Industry 4.0 is an evolving digital industrial age that utilizes advanced technologies, such as the IoT, robotics, and data analysis, to improve production efficiency. One of the main challenges for this transition is to ensure

efficient wireless connectivity between all of the parts involved.¹⁵ There needs to be an optimization of the wireless network at the network level to enable this. It involves optimizing the access points (APs) and other components of the wireless network, such as antennas, cabling, and other hardware. It would allow for better signal coverage, increased data throughput, improved scalability, and lower latency.²⁶ Additionally, the optimization of the wireless network would enable the use of advanced technologies, such as AI, machine-to-machine (M2M) communication, and other tools that are necessary to achieve the full benefits.²⁷ Network-level optimization focuses on improving the performance of the underlying communication network that serves as the backbone for Industry 4.0-enabled applications and systems. The main aim of network-level optimization is to reduce latency, optimize bandwidth utilization, and improve fault tolerance of all IoT devices connected to the system.²⁸ Network-level optimizations can be implemented in various innovative ways, including:

- Utilizing high bandwidth network topologies, such as mesh networks, optimized star networks, and ring networks.
- Implementing data compression algorithms for efficient data transmission.
- Utilizing M2M communication protocols, such as Bluetooth, Wi-Fi, and Zigbee to reduce latency.
- Implementing quality of service (QoS) techniques to ensure certain time-sensitive traffic is given priority over regular traffic.
- Optimizing traffic routing to ensure that packets always reach their destination in the shortest possible time.
- Setting up redundant links to provide business continuity during any unexpected interruptions or outages.

Sensor nodes can be powered by traditional mains electricity, solar energy, or batteries. Each option has its advantages and disadvantages in power. Mains electricity can provide a reliable source of power, but it also requires an external power source or wiring. Solar energy is a clean and renewable source, but its power is dependent on weather conditions such as sunlight. Batteries are relatively inexpensive but need to be periodically replaced, and charging takes up time and money. The power issue of the sensor nodes becomes a significant challenge. Sensor nodes require a sufficient and reliable source of power to work properly and operate at high efficiency. If the power issue is not considered properly, it may lead to data loss or malfunction of the system. It will reduce the accuracy

and efficiency of industrial processes, which will directly affect the enterprise's profits. It adopts wireless power transfer technologies to solve power issues. These technologies enable sensor nodes to be conveniently recharged autonomously without the need to replace or recharge the battery. Moreover, they can also reduce the security risks of cabling and wiring in the factory. The main contributions of the research are the following:

- Increase in data analysis efficiency: The proposed research will allow sensor nodes to process and analyze data more efficiently, leading to improved performance.
- Improved reliability and accuracy: The enhanced analytics built into the proposed research will help Sensor Nodes to be more reliable and accurate in their readings, resulting in improved performance.
- Improved power utilization: The proposed research will help to optimize power utilization in Sensor Nodes, allowing for improved performance by reducing energy consumption.
- Improved communication capabilities: By improving communication protocols and channels, Sensor Nodes can be more effectively integrated into Industry 4.0 systems, leading to improved performance.
- Improved scalability: The proposed research will allow Sensor Nodes to scale as needed to accommodate increased volumes of data in Industry 4.0, leading to increased performance.

The following is organized according to the paper's remaining sections. The most current research-related efforts are described in Section 2. Algorithms and the suggested model are presented in Section 3. The analytical discussion is given in Section 4, Section 5 provides the obtained results, and Section 6 discusses the comparison of the current and suggested models. Section 7 offers the conclusion and additional improvements to the suggested model.

2 | RELATED WORKS

Industry 4.0 is the fourth industrial revolution, focusing on automation, data exchange, and the IoT to create a more efficient, connected, and intelligent industry. Sensor nodes are an essential part of any Industrial 4.0 system, providing real-time data for decision-making. Here, some recent research works provide a clear idea about the performance of sensor nodes in Industry 4.0.

Wang et al.²⁹ have discussed the Efficient Privacy-Preserving User Authentication Scheme with Forward Secrecy for Industry 4.0; it is a secure authentication

scheme that provides enhanced privacy for users in the digital age. This scheme allows users to securely authenticate with an online service, such as an industrial machine while preserving the privacy of their credentials. The scheme uses a forward secrecy technique to ensure that data is not leaked even if the encryption key is compromised. The scheme generates a unique one-time key (OTK) for each user. This key encrypts the user's credentials and is only stored on the user's device. The encrypted credentials are then sent to the server, which verifies the credentials and grants access to the user. The server stores the encrypted data in a secure database and can respond to requests from the user's device. If a malicious user tries to gain access to the encrypted data, the encryption key is required to decrypt it. It means that the malicious user must have access to the OTK to gain access. The Efficient Privacy-Preserving User Authentication Scheme with Forward Secrecy for Industry 4.0 provides enhanced security and privacy for users while allowing them to authenticate with online services securely. This scheme is an excellent example of how digital technologies can be used to protect user data and enhance privacy. Haque et al.³⁰ have discussed the ambient self-powered cluster-based wireless sensor networks (ASP-CSWSNs), which are wireless sensor networks used in Industry 4.0 applications. ASP-CSWSNs are designed to be reliable, self-powered, and energy-efficient. They are based on the concept of clustering, meaning that the network nodes are organized into groups or clusters for efficient communication and data exchange. Each cluster comprises several nodes connected, and the nodes communicate with each other using a wireless protocol. The ASP-CSWSNs are used for different purposes in Industry 4.0 applications. They can be used for monitoring, control, and data collection from different systems in a factory or industrial environment. The nodes in the network are self-powered and can be powered using energy harvesting techniques, such as solar panels or thermoelectricity. The nodes in the network also feature low-power communication protocols, such as bluetooth low energy (BLE) and Zigbee, which allow for efficient data transfer between the nodes. The ASP-CSWSNs are ideal for Industry 4.0 applications because they are reliable, energy-efficient, and self-powered. They can also be easily deployed and monitored, making them an ideal choice for use in industrial settings. Yan et al.³¹ have discussed industrial big data, which is generated from the IoT and other connected systems in industrial settings. This data can be used to improve processes, reduce downtime, and increase safety. In an Industry 4.0 environment, big industrial data can enable predictive maintenance, automate processes, and enable remote monitoring and control.

Such data can provide insights into how the industrial environment functions and can be used to diagnose and identify problems to be addressed. With the help of AI and machine learning, it can even optimize operations and predict future trends.

Devesh et al.³² have discussed that Industry 4.0 is the fourth industrial revolution based on cyber-physical systems (CPS) and the IoT. CPS and IoT enable machines, devices, and systems to be connected to the internet, allowing them to share data and collaborate to complete tasks. CPS are computer-controlled systems that monitor physical processes and make decisions based on the data they collect. It enables machines to operate autonomously and make decisions without human intervention. It also allows machines to work together to optimize performance and reduce operational costs. IoT is the network of physical objects embedded with electronics, software, sensors, and network connectivity that allow them to collect and exchange data. IoT devices can be used to monitor and control physical processes and collect and analyze data. CPS and IoT in Industry 4.0 have enabled excellent connectivity, automation, and data-driven decision-making. It has resulted in increased efficiency and cost savings for companies and improved safety and quality control. CPS and IoT can also create new products and services, such as predictive maintenance and remote monitoring. It has enabled companies to create new sources of revenue and remain competitive in an ever-changing marketplace. Wan et al.³³ have discussed the Software-defined industrial Internet of Things (SDIIoT), which is a term used to describe the integration of M2M communications, cloud computing, and analytics that enable the efficient, cost-effective, and secure management of industrial-level processes and operations. By utilizing the power of the IoT and cloud computing, SDIIoT allows manufacturers to enhance their existing systems and operations with software-defined control, automation, and analytics. It, in turn, enables them to increase their processes' efficiency, accuracy, and productivity while reducing operational costs. SDIIoT is an integral part of Industry 4.0, the fourth industrial revolution. The enabling technology allows machines to communicate with each other and other systems, enabling data-driven decision-making, which is the cornerstone of Industry 4.0. By leveraging analytics, SDIIoT can help industrial organizations optimize their processes, increase efficiency, and reduce costs. By connecting machines, sensors, and other devices to the cloud, SDIIoT provides the means to deploy applications that can monitor and manage operations in real time. This data can then be used to make informed decisions and improve operations. Leonardi et al.³⁴ have discussed the novel medium

access strategy for LoRa in Industry 4.0 applications, which is a strategy that combines the benefits of LoRa technology with the industrial applications of Industry 4.0. The strategy uses a distributed and hierarchical scheduling approach to maximize the efficiency of LoRa transmissions in industrial environments. It is based on the fact that LoRa has a much lower power consumption than other communication technologies and a more extended range. The proposed strategy is aimed at taking advantage of the low power consumption of LoRa while increasing the throughput and reliability of the transmission. The strategy also utilizes an algorithm to adjust the transmission parameters according to the environment to maximize the transmission's efficiency. This strategy can improve communication performance in industrial applications, such as in manufacturing plants, warehouses, and other areas where data transmission is critical.

Kumar et al.³⁵ have discussed Industry 4.0 as the fourth industrial revolution, characterized by the use of digital technologies, such as the IoT, Big Data, and AI to improve efficiency, productivity, and quality in the manufacturing industry. Efficiency 4.0 applies these digital technologies to improve production efficiency across the entire value chain. It includes using data-driven automation, predictive analytics, and machine learning to optimize processes, reduce waste, and increase throughput. The goal of Efficiency 4.0 is to create a more efficient, reliable, and cost-effective production process. The ultimate goal is to enable companies to produce more with fewer resources, leading to increased profitability and sustainability. Logeshwaran et al.³⁶ have discussed the Smart Load-Based Resource Optimization Model, which is a resource optimization model designed to enhance the performance of device-to-device (D2D) communication. It uses a combination of predictive analytics and intelligent resource allocation to optimize the allocation of resources for D2D communication. The model uses historical data to predict the future load of D2D communication and then adjust the resource allocation accordingly. It allows the model to dynamically adjust the resources allocated to D2D communication based on the current and predicted load. The model also considers the QoS requirements for each device and can adjust the resource allocation accordingly. The Smart Load-Based Resource Optimization Model is designed to improve the performance of D2D communication by minimizing latency, jitter, and packet loss, maximizing throughput and reliability. Preuveneers et al.³⁷ have discussed the intelligent industry of the future as an ambitious concept that envisions a world where machines are used to automate processes and create new business opportunities. The concept calls for creating intelligent systems

that can learn, adapt, and respond to their environment to increase efficiency, reduce cost, and improve overall productivity. It could include using AI, machine learning, cognitive computing, robotics, and the IoT. As these technologies become more advanced, they will be used to automate processes and create new products, services, and business models. It could revolutionize how businesses operate and lead to a new era of industrialization.

Faheem et al.³⁸ have discussed the cross-layer approach for Big Data Gathering for Active Monitoring and Maintenance in the Manufacturing Industry 4.0, which is a framework that facilitates the use of Big Data to monitor and maintain the production process of a manufacturing plant. The cross-layer approach is based on an integrated, holistic system for capturing, analyzing, and applying real-time data. It is designed to enable the active monitoring of production processes and the continuous maintenance of equipment and systems. This approach integrates data from the different layers of the manufacturing process, including the physical layer (i.e., sensors and actuators), the embedded layer (i.e., embedded systems and controllers), the network layer (i.e., data communication networks), and the software layer (i.e., analytics and decision-making). The cross-layer approach is designed to enable real-time analysis of data from all these layers, identify potential problems, predict future problems, and implement preventive maintenance. This approach is expected to improve the efficiency and effectiveness of the manufacturing process, leading to better quality control and improved product quality. Blanco-Novoa et al.³⁹ have discussed the practical evaluation of commercial industrial augmented reality (AR) systems in an Industry 4.0 shipyard, which involves assessing the effectiveness and efficiency of these systems in the shipyard environment. Specifically, this evaluation should focus on how the AR systems improve safety, productivity, and quality in the shipyard. The evaluation should also consider how the AR systems integrate with existing systems and infrastructure and how users interact. Sherazi et al.⁴⁰ have discussed that energy harvesting in LoRaWAN is a technology used to harvest energy from ambient sources, such as light, heat, vibration, and RF. This harvested energy can then be utilized to power LoRaWAN networks and devices. In LoRaWAN, energy harvesting is used to reduce energy consumption by devices, which enables longer battery life and more reliable communication. Additionally, energy harvesting can reduce the cost of powering and maintaining LoRaWAN networks and devices. This technology could enable low-power, cost-effective, and long-range IoT solutions. Souza et al.⁴¹ have discussed that the optically powered wireless sensor node is a wireless sensor network node that uses optical

energy as its primary power source. These nodes are designed to be used in industrial IoT applications, where they can collect data from a wide range of sensors and send it back to a central hub. The nodes use light-emitting diodes (LEDs) to generate electrical energy, which can be used to power the nodes and the sensors. Optically powered wireless sensor nodes are an attractive solution for industrial IoT applications, as they provide a reliable, low-cost means of collecting data from various sensors. Additionally, they require little to no maintenance and are easy to install.

Mistarihi et al.⁴² have discussed that the Energy-Efficient Bi-Objective Optimization based on the Moth-Flame Algorithm (EEBFMO) is an optimization algorithm used for the selection of cluster heads (CHs) in a wireless sensor network (WSN). EEBFMO is an improved version of the Moth-Flame Algorithm (MFA), which balances two objectives—energy efficiency and load balancing—when selecting CHs. EEBFMO is designed to optimize the network by selecting the most suitable CHs to improve energy efficiency and reduce network load. EEBFMO can also be used for other multiobjective optimization problems. Alfawaz et al.⁴³ have discussed a modified Rat Swarm Optimization Based Localization Algorithm for Wireless Sensor Networks, which is a localization algorithm that combines the Rat Swarm Optimization (RSO) algorithm with a cooperative sensing and localization scheme. The RSO algorithm is used to optimize the distribution of anchors around the target area, which improves the accuracy of localization. The cooperative sensing and localization scheme is used to provide additional data for tracking and localizing the target in an efficient and highly accurate manner. This algorithm can be used for various types of Wireless Sensor Networks, such as ZigBee, Wi-Fi, and so on. Hammad et al.⁴⁴ have discussed an Industry 4.0 approach designed to help manufacturers adopt secure and personalized production systems that use cloud-based networks to integrate multiple devices and IT systems. This security framework consists of three phases: risk assessment and risk management, security architecture, and security implementation. The risk assessment and risk management phase helps to identify security-related risks and design robust security policies to mitigate them. The security architecture phase is used to design a secure network architecture for the Industry 4.0 manufacturing system that includes authentication, authorization, encryption, and monitoring methods. The security implementation phase helps to deploy the secure network infrastructure across multiple devices and systems. Lilhore et al.⁴⁵ have discussed how the model is optimized by using convolutional neural network (CNN) and long short-term memory (LSTM)

architectures and transfer learning techniques. The optimized model accurately detects abnormal network behavior without relying on massive computational resources or additional data collection. By leveraging transfer learning, the model can provide sharper insights from fewer training samples and consequently reduce the required training time. With the help of this model, incoming network data is quickly analyzed into meaningful representation, and based on the comprehensive analysis, further measures are taken to detect any potential intrusion. The comprehensive analysis is shown in Table 1.

From the above comprehensive analysis, the following issues were identified:

- **Optimize power consumption:** It is essential to optimize power consumption. Using low-power electronics and efficient power management techniques makes the sensor nodes more efficient and reliable.
- **Improve data processing:** It is essential to improve data processing capabilities. The data can be processed more quickly and accurately using advanced algorithms.
- **Increase communication range:** It is essential to increase the communication range. The range can be increased by using techniques, such as mesh networking and multiple-input multiple-output (MIMO) communication.
- **Enhance security:** It is essential to enhance the security of the sensor nodes. By using encryption and authentication techniques the security can be improved.
- **Reduce latency:** It is essential to reduce data transmission latency. The latency can be reduced by using techniques, such as buffering and compression.

It is essential to ensure that they are reliable and efficient. It can be achieved using advanced sensors explicitly designed for Industry 4.0. These sensors should be designed with high accuracy, low power consumption, and long-term durability. Additionally, sensor nodes must be designed to be interoperable with other Industry 4.0 technologies, such as edge computing, AI, and robotic process automation. The novelty of the proposed model is to enhance the performance of sensor nodes in Industry 4.0 and its use of a distributed optimization algorithm to reduce communication overhead. This algorithm uses a combination of reinforcement learning and a distributed optimization process to enable sensor nodes to learn how to optimize their energy consumption. Additionally, the framework allows for incorporating environmental data, such as temperature and humidity, to improve the system's energy efficiency

further. It enables sensor nodes to remain active for extended periods, thereby improving the performance of the sensor network.

- **Intelligent sensing:** Smart sensing technology utilizes sensors for data collection, analysis, and interpretation to anticipate and make real-time decisions. It also enables predictive maintenance and process optimization.
- **Edge Communication:** It enables sensor nodes to be connected directly to the cloud, enabling data processing and decision-making at the edge. It reduces latency and improves performance.
- **Wireless communication:** It enables sensor nodes to communicate with each other securely and reliably. It facilitates instant communication between devices and enables real-time data collection and analysis.

The network architecture should be designed to optimize data transmission and reception. It includes wireless network protocols, such as BLE, Wi-Fi, and 5G. Additionally, edge computing and AI can help reduce latency and improve the accuracy of data transmissions. It is essential to use secure protocols, such as TLS and IPSec. Also, secure authentication and encryption technologies can help protect data from unauthorized access. Additionally, it is important to regularly audit and test the networks and systems to ensure they remain secure and compliant.

3 | METHODOLOGY

Energy optimization in industrial automation is the process of reducing energy consumption while maximizing productivity. It is designed to provide cost savings, efficiency, and environmental benefits. Industrial automation technologies, such as robots, programmable logic controllers, and distributed control systems provide tools and technologies to reduce energy usage while increasing production and yields. Energy optimization is achieved by using intelligent energy data analysis and predictive analytics, which allow manufacturers to understand their energy usage patterns to identify and apply the most effective energy conservation measures. Additionally, energy-efficient automation solutions provide further energy savings by enabling manufacturers to turn off machines and equipment when not in use. Finally, energy optimization also helps increase the efficiency of existing equipment by providing optimized control strategies and system architectures that reduce energy use. The industrial energy optimization block diagram is shown in Figure 1.

TABLE 1 Comprehensive analysis.

Authors	Year	Advantages	Limitations
Wang et al. ²⁹	2022	It ensures secure access and communication for users while minimizing the chances of interception by unauthorized users.	The user must have prior knowledge of the authentication methods employed by the scheme.
Haque et al. ³⁰	2021	Autonomous energy generation and utilization in the sensor nodes allow for long-term, continuous monitoring of industrial processes.	Limited coverage and communication range due to power problems in the sensor nodes.
Yan et al. ³¹	2017	It can improve existing operations, increase operational efficiency, and reduce the cost of maintenance.	There is a potential risk of data leaks or privacy issues related to data usage.
Devesh et al. ³²	2020	Increased efficiency and sustainability through automated data-driven processes and operations.	Security concerns over data sharing and storage within the networks.
Wan et al. ³³	2016	It allows for better monitoring and control of industrial operations for efficiency and automated decision-making.	Security remains an issue due to data ownership and access controls.
Leonardi et al. ³⁴	2018	Low power consumption and cost-effectiveness.	Limited coverage and low data rate.
Kumar et al. ³⁵	2019	Increased industrial efficiency through the utilization of advanced digital technologies.	High cost of adoption due to the need for costly hardware, software, and other necessary resources.
Logeshwaran et al. ³⁶	2023	The model can reduce transmission time and help balance the power consumption of the nodes.	The model will incur additional overhead in terms of computation and energy.
Preuveneers et al. ³⁷	2017	It promotes collaborative innovation between industry leaders, academics, and research practitioners.	High dependency on complex technology, which can be confusing to understand and implement.
Faheem et al. ³⁸	2021	Cross-layer approach provides integrated detailed information about various behaviors of participants in different layers of the network.	Cross-layer approach raises security and privacy issues for active monitoring and maintenance in the manufacturing Industry 4.0.
Blanco-Novoa et al. ³⁹	2018	Augmented reality systems can allow for a comprehensive analysis and feedback of industrial operations.	Augmented reality systems are costly, which can limit their availability in an Industry 4.0 shipyard.
Sherazi et al. ⁴⁰	2018	Offers energy efficiency and low operational costs to meet high-performance requirements for Industry 4.0.	Limited in range and power output, which may restrict the performance of some applications.
Souza et al. ⁴¹	2021	Optically powered wireless sensors can provide self-sustaining power for several years without on-site personnel visits or battery changes.	The high cost of optical sources and photovoltaic cells can increase the cost of large-scale deployment.
Mistarihi et al. ⁴²	2023	It offers optimal solution coverage with minimum power consumption.	The complexity increases rapidly due to the number of network nodes.
Alfawaz et al. ⁴³	2023	It works well in most wireless sensor network environments, with low energy consumption and high localization accuracy.	It is also computationally expensive with large quantities of agents and has difficulty dealing with dynamic environments.
Hammad et al. ⁴⁴	2023	It allows for secure integration and communication in a network-based manufacturing system.	It does not guarantee protection of confidential data.
Lilhore et al. ⁴⁵	2023	It is capable of detecting anomalous behavior in complex and evolving environments.	It is heavily dependent on the quality of data sources and has a high computation cost.

It is a tool that can be used to improve the performance of sensor nodes in Industry 4.0. The energy optimization framework (EOF) consists of two primary components: a power management system and an optimization algorithm. The power management system is responsible for providing continuous power input to the sensor nodes so that they can perform their duties without interruption. On the other hand, the optimization algorithm is used to look for ways to improve the energy efficiency of the nodes. It does this by considering the activity of the nodes, the distance between them, the data transmission loads, and other factors that may affect the power supply's efficiency. The EOF can be used to identify new patterns and experiments that may lead to further improvements in the energy efficiency of sensor nodes. Ultimately, this helps to reduce energy expenditure and costs while ensuring that all sensor nodes remain operational, reliable, and accurate.

3.1 | Power management system

A power management system is a system that helps monitor and manage the total energy consumption and consumption of energy sources to maximize energy savings and efficiency. It ensures efficient utilization of energy resources and makes sure that wastage of energy is minimized. This system enables energy management and monitoring of equipment, devices, and processes, thereby helping to reduce energy consumption, enhance efficiency, and improve environmental performance. It also enables optimizing energy usage and effective scheduling and energy consumption prediction. This system can identify areas of excess energy and opportunities to optimize energy usage, develop new strategies, and assist with decision-making. The power management system is shown in Figure 2.

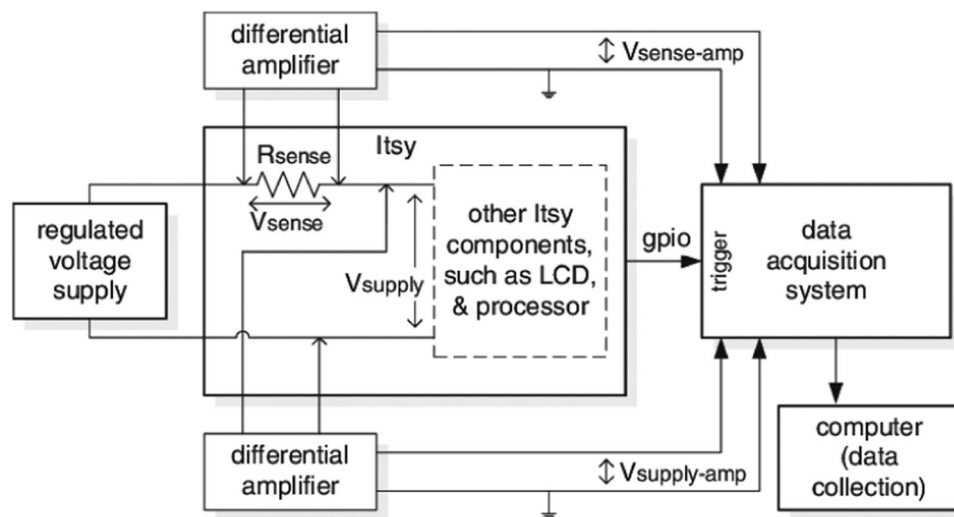


FIGURE 1 Industrial energy optimization block diagram.

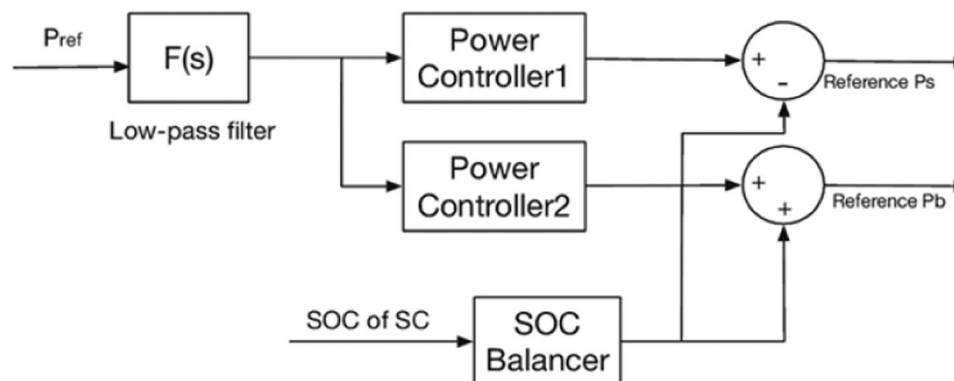


FIGURE 2 Power management system.

It is an integrated system that enables efficient and effective control of energy consumption in industrial settings. The system monitors and regulates the energy usage of equipment to reduce energy consumption and optimize energy consumption for maximum efficiency. The system incorporates state-of-the-art monitoring and control devices to manage energy resources to minimize energy consumption actively. The system also uses advanced analytics to monitor and predict energy usage in the production process to improve efficiency and reduce the cost of energy consumption. Furthermore, the system has built-in adaptive control algorithms that can be used to adjust production processes to reduce the energy footprint further. It provides recommendations for employers on reducing energy costs and optimizing energy usage based on the data collected. The power management system for this model helps employers optimize their energy consumption and reduce costs by utilizing data-driven technologies and advanced analytics.

3.2 | Optimization algorithm

The optimization algorithm is a set of rules that allow for the efficient and cost-effective utilization of energy resources in industrial processes to maximize the cost and environmental benefits. The external environmental factors, such as legislation, market prices, and local conditions, can be considered and integrated into the decision-making process. An optimization algorithm can be used to determine the most efficient ways of using energy resources through dynamic optimization of the cost, environmental benefits, and other factors. It may include using technologies, such as AI, machine learning, and optimization algorithms to identify process changes that reduce energy use while increasing efficiency and producing cost-saving and environmental benefits. Additionally, it could be optimized for the long term by ensuring that the production rate, energy used, and money saved are maintained regularly. Algorithm 1 expresses the energy optimization process.

Algorithm 1. Energy optimization algorithm

1. Input: No. of Sensor nodes ($S(n)$), Input Energy (E_i)
2. Output: SET_CE;//Set of energy clusters
3. For each node (a_i*b*c)
4. Begin
5. Identify the nearest nodes of a_i ;
6. Compute the energy utilization;
7. Measure the Network load $L(a_i) = z_1 * E(a_i)$;

8. $CL = L(a_i)$;
 9. End
 10. Sort the CL order in Ascending manner;
 11. While CL is not equal to 0
 12. Begin
 13. $a_i = (CL/\text{Energy utilization of the initial node from } a_i)$
 14. Remove the utilized energy from the total energy;
 15. End
-

These algorithms analyze large volumes of data, such as energy consumption relating to each facility, and identify opportunities to reduce energy waste and improve efficiency. For example, they may detect when an electricity-intensive machine needs to be shut down briefly to allow other machines to take on a higher load or when a particular power configuration can be adjusted to reduce energy use. Optimization algorithms also enable the integration of other energy sources, such as solar power, wind power, and other renewable energy sources, into a facility's energy network. Furthermore, optimization algorithms can also optimize energy flows within a facility, considering the availability of resources, cost structure, and user preferences. Finally, optimization algorithms can also be used for predictive maintenance, predicting future energy needs and taking preemptive measures to address them.

It can optimize energy consumption and improve energy efficiency (Figure 3). This framework is designed to meet various industries' needs regarding energy saving and cost reduction. It provides an integrated energy optimization approach that helps achieve the desired results. It examines the energy consumption requirements of an industrial facility and suggests methods to reduce energy consumption. It also identifies specific areas in the facility where energy can be saved and helps implement energy optimization strategies. It integrates energy analytics, data analytics, energy monitoring, fault detection, and energy management systems. It provides tools to analyze and optimize energy usage. It also helps integrate multiple energy sources and systems to produce an optimal energy management plan. Lastly, it helps monitor the facility's energy performance using automated data collection, analytics, reporting, and visualization tools. It is also an effective tool for companies to reduce their energy costs, enhance the energy efficiency, and reduce their environmental footprint.

The algorithm's environmental robustness is determined by the degree to which its performance remains consistent when exposed to different environmental variables, such as changing weather, available resources,

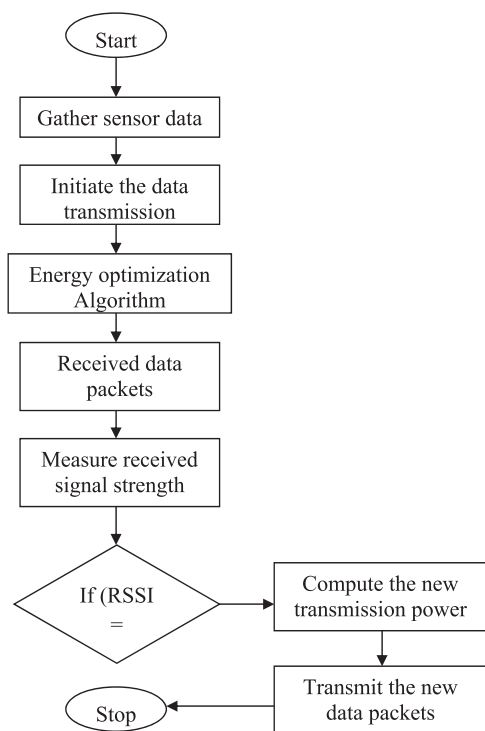


FIGURE 3 Functional flow diagram for the proposed framework.

and varying user behaviors. If the algorithm is designed to be efficient and reliable under different conditions, then it is considered to be environmentally robust. It means that the algorithm should be able to handle new or unfamiliar environmental conditions without negative impacts on its performance. For example, an energy optimization algorithm designed to work in a cold environment should remain effective in a hot environment and vice versa. The algorithm should also be able to effectively adjust its performance and adapt to different changes in the environment over time.

4 | ANALYTICAL DISCUSSION

The application of analytics in Industry 4.0 is seen as critical in helping optimize energy use in industrial environments. Analytics provide the platform to gain data-driven insights on energy efficiency and, thus, facilitate improved decision-making. By monitoring energy use over time, companies can see where to conserve energy and increase efficiency. It allows companies to determine which processes are using more energy than they should or identify areas where energy is wasted. Using analytics in energy optimization allows companies to create accurate forecasting models that predict future energy use. These predictive models allow

for more informed and strategic decisions about energy use. The analytical discussion also helps companies understand changing energy use patterns and identify potential problems or opportunities. By having visibility into energy use, companies can better manage their use and make informed decisions that help optimize costs and meet their energy-efficiency goals.

4.1 | Improved industrial sensing

Smart sensing is designed to improve energy usage efficiency in industrial applications. The framework comprises three parts—sensor-based sensing, data analytics, and intelligent process automation (IPA). The sensor-based sensing gathers data from multiple sources and provides insights into the energy performance of an industrial process. Data analytics then uses this real-time data to identify energy wastages and process optimization opportunities. The IPA uses the data insights to automate processes and execute efficient energy usage recommendations to ensure optimal energy is consumed at the right time. Reduced energy wastage and improved process efficiency lead to optimized energy utilization and significant cost savings in industrial operations. It helps to reduce energy wastage and improve energy utilization, increasing the overall efficiency of industrial applications. Intelligent sensors help monitor energy usage and detect inefficiencies in a production environment while increasing the visibility of energy data. This data can then drive automated decisions that optimize energy utilization across the supply chain. Intelligent sensing also offers the ability to detect specific energy components and costs, such as electricity, gas, and cooling, which can be used to formulate energy policies and strategies. Intelligent sensors have already provided value in real-time monitoring of energy usage in Industry 4.0 and have enabled better forecasting of potential disruptions in production, such as machine breakdowns, which could lead to a significant waste of energy. Intelligent sensors have also allowed for more creative optimization opportunities, such as passing electrical impulses to machines, which intelligently define and track parameters, such as operating time, load, and temperature for greater accuracy of energy utilization.

4.2 | Improved edge node communication

Edge node communication is a critical part. It enables real-time data collection, analysis, and decision-making at the point of production. By collecting sensor data,

edge nodes extract information on energy use, resource availability, and other production variables and generate actionable insights on the best ways to optimize the process and increase efficiency. Additionally, edge nodes provide a standard communication protocol for devices to communicate and control each other. This communication facilitates proactive monitoring and control, allowing for early identification of potential waste and inefficiencies. With edge node communication, energy optimization in Industry 4.0 can be achieved quickly and efficiently, providing cost savings and environmental benefits. It focuses on improving the ability of edge nodes to communicate with each other to improve the effectiveness and efficiency of energy utilization. This framework helps reduce energy costs by maximizing edge node resources while minimizing power consumption. It enables the edge nodes to communicate with each other, allowing them to exchange essential data, such as energy consumption and availability, operating conditions, and power costs. The framework also helps identify anomalies in the system and suggest appropriate measures to resolve them. It helps ensure that energy resources are utilized optimally. The framework also provides predictive analysis, which enables proactive energy management practices. It allows for better energy utilization in a cost-effective way. The edge node communication helps to optimize energy utilization in smart factories and buildings, resulting in more efficient energy utilization and cost savings.

4.3 | Improved wireless communication

Wireless communication technology has become increasingly important in Industry 4.0, enabling companies to collect and transmit data from machinery and sensors across an IoT network in real time. Wireless communication can be used to optimize energy usage and reduce operating costs. Industrial wireless networks can monitor and adjust the settings of machinery and equipment to maintain energy health and optimize energy consumption. Speed, temperature, and pressure can be adjusted to conserve energy and reduce excessive energy consumption. Additionally, wireless sensors can continuously monitor energy usage and offer managers real-time energy data. This data can inform managers when it is time to move production operations to a new machine so that operations are as energy-efficient as possible. It helps companies collect data from machines and sensors in real time, which can be used to adjust settings and conserve energy. Wireless sensors help managers

monitor and analyze energy usage and adjust their operations as needed to optimize energy consumption. It connects different processes between machines, objects, and people, creating a common language and allowing them to interact. This technology is becoming increasingly important as the Industry 4.0 revolution progresses. It enables real-time data transmission to provide a better understanding of the process and to monitor and control energy utilization accurately. Wireless communication also helps ensure optimal connectivity between machines and provides access to a vast array of data sources, including sensors and actuators, which are necessary to improve energy efficiency. It is achieved by providing consistent and reliable communication, which allows the industry to make more informed decisions when managing energy. By using the latest in cloud computing, edge computing, and distributed systems, wireless communication technology helps to ensure the smooth and reliable operation of systems efficiently. Wireless communication is also being used to facilitate the integration of renewable energy sources into traditional energy systems and automate the management and optimization of energy utilization. It allows companies to become more flexible and efficient in managing energy.

5 | RESULTS

The proposed EOF has been compared with the existing energy-efficiency clustering (EEC), genetic algorithm (GA), QoS-aware routing protocol (QARP), and Mobile sinks-based QoS-aware data gathering protocol (MQRP). Here the matlab r2021a has the simulation tool used to execute the results.

Data set: Sensor nodes fault detection data set⁴⁶ used in this research. Totally 4812 samples were collected. In this, 80% (3850 samples) of the samples were used for training purposes, and 20% (962 samples) of the samples were used for testing purposes.

5.1 | Computation of sensitivity (S)

The sensitivity is paramount for industrial automation. It is an essential part of the optimization process since it allows the gain from the energy savings produced to be quickly and thoroughly evaluated. Sensitivity refers to the ability to detect changes in energy costs as different system components (e.g., production line setup or the amount of power consumed by a piece of equipment) are altered. It allows for continual optimization of the system

to maximize efficiency in production, electricity usage, and, ultimately, the cost of goods produced. Table 2 expresses the evaluation of sensitivity between the existing and proposed models.

Figure 4 shows the evaluation of sensitivity. In an estimation phase, EEC reached 59.94%, GA obtained 53.77%, QARP reached 86.67%, and MQRP obtained 78.19% sensitivity. The proposed EOF obtained 97.34% sensitivity. It also allows for an improved understanding of the system components that have the most significant impact on energy costs so that resources may be

TABLE 2 Evaluation of sensitivity (in %).

Inputs	EEC	GA	QARP	MQRP	EOF
100	57.13	50.78	83.89	74.58	95.21
200	57.46	52.28	84.48	76.45	96.25
300	58.80	53.39	85.46	77.28	96.38
400	59.94	53.77	86.67	78.19	97.34
500	60.99	54.78	87.81	79.11	96.91
600	61.70	55.71	88.92	80.44	98.15
700	63.00	56.71	89.62	81.31	98.26

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

dedicated to those areas to drive the most significant energy savings. It should be regularly monitored and revised to ensure that energy sensitivity is optimized to its fullest extent.

5.2 | Computation of false discovery rate (FDR)

The FDR is a metric used to quantify the rate at which false positives occur among a set of results. The FDR measures the accuracy of industrial automation. In this context, the FDR is calculated by taking the total number of false results (false positives) identified by the optimization framework, divided by the number of all results generated, which can include true and false results. The resulting number, usually expressed as a percentage, tells us how accurate the optimization framework is at correctly identifying the energy-saving opportunities in a given system. Table 3 expresses the evaluation of the FDR between the existing and proposed models.

Figure 5 shows the evaluation of the FDR. In an estimation phase, EEC reached 69.58%, GA obtained 64.12%, QARP reached 80.12%, and MQRP obtained 65.89% FDR. The proposed EOF obtained 91.36% FDR. It measures the rate of false positives when using a

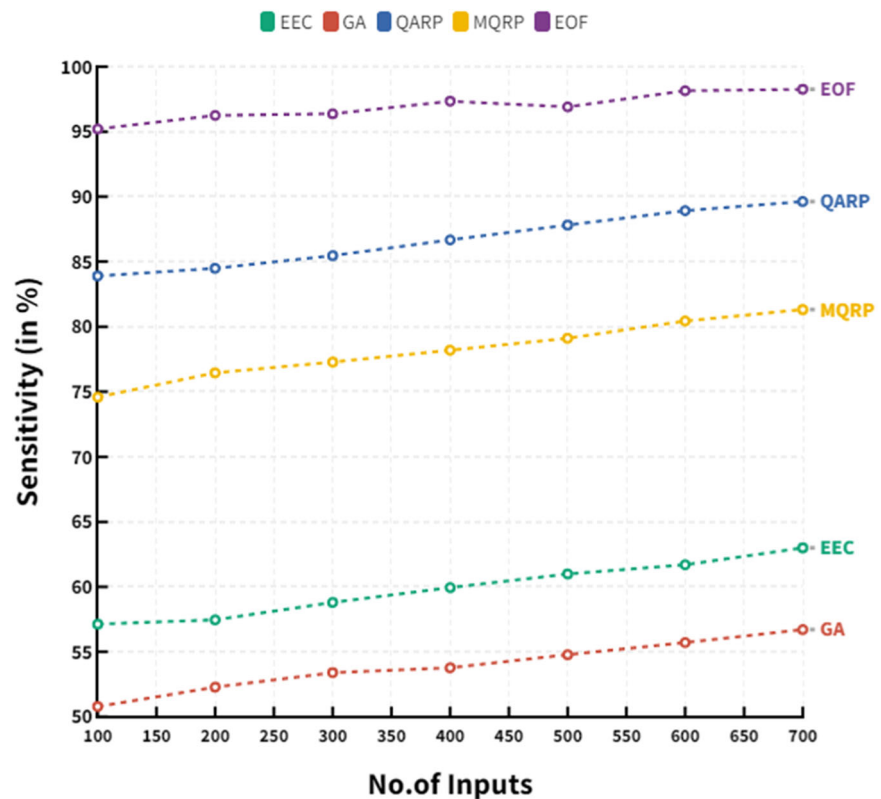


FIGURE 4 Evaluation of sensitivity. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

hypothesis test in multiple comparisons. The FDR helps to determine which energy optimization methods are effective and which are ineffective by weighing the rate of falsely claimed efficient solutions versus the rate of practical solutions. A higher FDR indicates that more efficient solutions are likely to be rejected, leading to a loss in energy efficiency. A lower FDR suggests that most of the efficient solutions that are tested are likely to be supported, leading to improved energy efficiency. The FDR also ensures that over-optimization is avoided,

making it easier to identify cost-effective and sustainable solutions. With the help of the FDR, it becomes easier to identify the best solutions and achieve optimal energy efficiency gains within the framework of Industry 4.0.

5.3 | False omission rate (FOR)

It ensures that the energy optimization strategies and strategies employed provide the desired energy savings. FOR is a measure of the number of times a detected peak load fails to be considered for optimization, or reduced in energy use, divided by the total number of peak loads eligible for optimization or reduction. Table 4 expresses the evaluation of the FOR between the existing and proposed models.

Figure 6 shows the evaluation of the FOR. In an estimation phase, EEC reached 40.33%, GA obtained 39.20%, QARP reached 46.79%, and MQRP obtained 26.65% FOR. The proposed EOF obtained 11.27% FOR.

The higher the FOR rate, the less effective an optimization strategy is in optimizing energy use. It is important to note that FORs depend on the optimization strategies employed and the criteria used to identify peak loads. It can be monitored by tracking the FOR, and optimization strategies can be improved.

TABLE 3 Evaluation of false discovery rate (in %).

Inputs	EEC	GA	QARP	MQRP	EOF
100	70.83	68.32	85.22	67.37	91.31
200	70.67	67.12	83.60	67.50	91.34
300	69.93	65.47	81.80	66.23	91.34
400	69.58	64.12	80.12	65.89	91.36
500	69.13	62.69	78.41	65.32	91.37
600	68.68	61.27	76.70	64.75	91.39
700	68.23	59.84	74.99	64.18	91.40

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

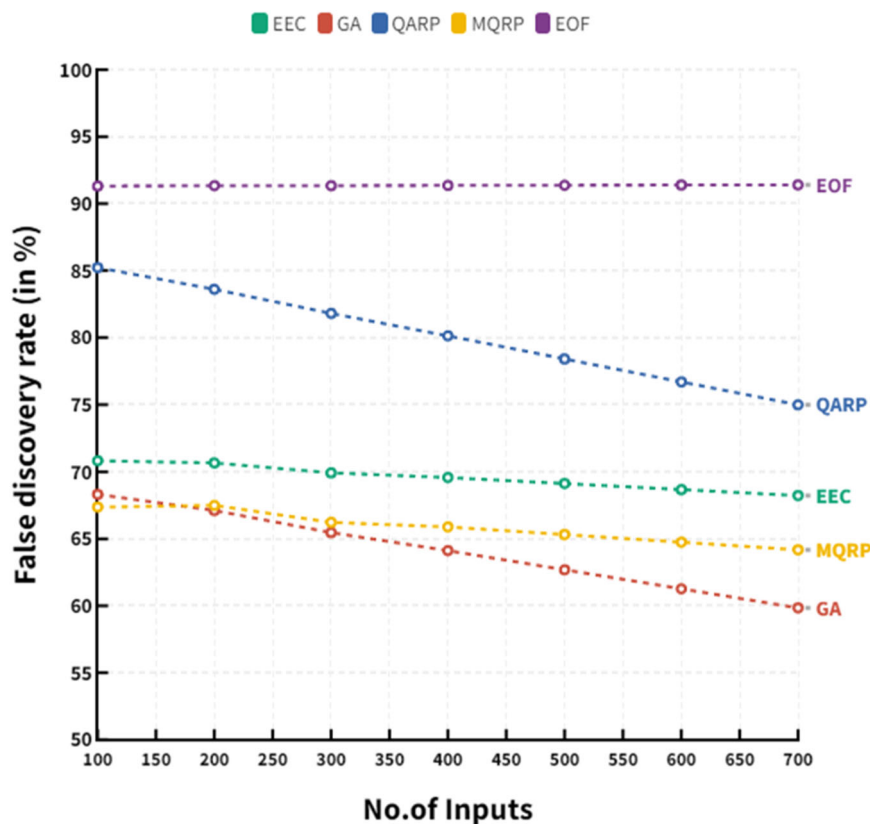


FIGURE 5 Evaluation of false discovery rate. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

5.4 | Computation of prevalence threshold (P_{th})

The prevalence threshold is a crucial metric in any industrial automation system that optimizes energy use. It is the threshold at which the system will begin to shed load to conserve energy. This threshold is based on the unmet demand or disruption incurred if no action was taken. If the demand exceeds the threshold, the system will begin to reduce grid demand to keep the grid balanced and reduce system disruptions. This level of shedding can also be used

TABLE 4 Evaluation of false omission rate (in %).

Inputs	EEC	GA	QARP	MQRP	EOF
100	37.86	45.06	36.52	36.79	11.05
200	36.20	39.20	43.36	31.38	11.15
300	35.75	40.34	44.65	29.89	11.22
400	40.33	39.20	46.79	26.65	11.27
500	39.27	36.84	50.85	23.20	11.35
600	39.97	35.20	54.06	20.01	11.43
700	40.67	33.55	57.27	16.82	11.50

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

to reduce utility costs while maintaining system stability. Table 5 expresses the evaluation of the prevalence threshold between the existing and proposed models.

Figure 7 shows the evaluation of the prevalence threshold. In an estimation phase, EEC reached 72.13%, GA obtained 75.49%, QARP reached 80.03%, and MQRP obtained a 75.18% prevalence threshold. The proposed EOF obtained a 90.53% prevalence threshold. It is set through a combination of engineering calculations, analysis of the system's load profile, and an understanding of the sensitivity of the system's components. Once the prevalence threshold has been set, the system can be monitored. The shedding can be adjusted to maintain the overall system efficiency while minimizing the impact of unmet demand or disruption.

5.5 | Computation of threat score (TS)

The threat score is calculated based on the security threats to which the framework is exposed. It is done by taking the calculated threat level and multiplying it with a “threat weight,” consisting of a numeric value that reflects the relative importance of the vulnerability. The threat score may include various components, such as the number of different threat sources, the magnitude of the threat, and the exploitability (known as “attack surface”) of each

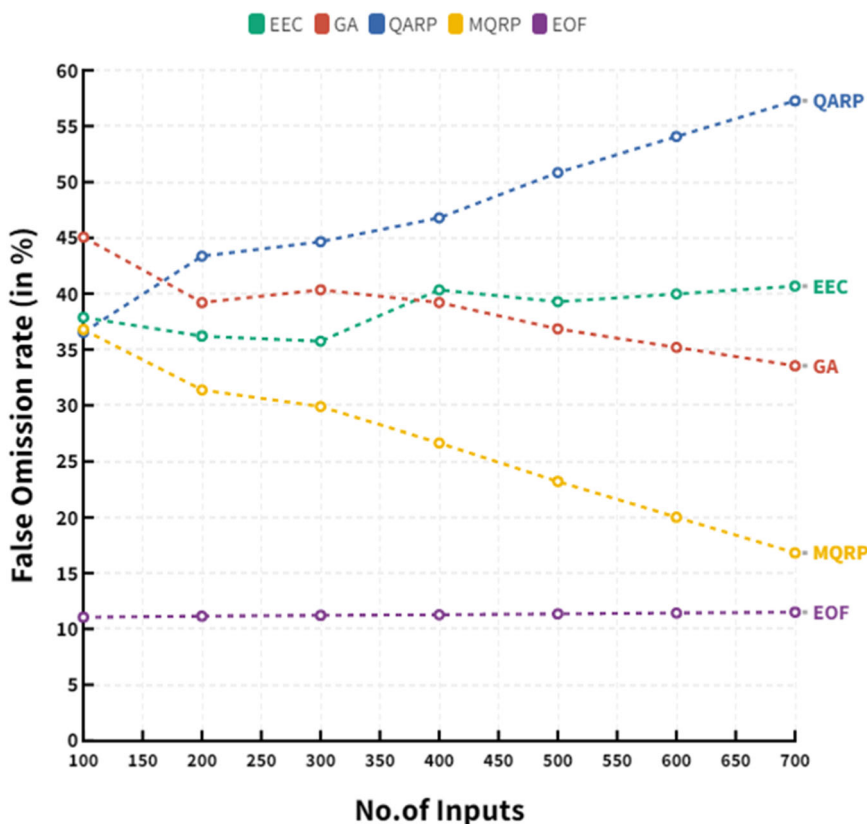


FIGURE 6 Evaluation of false omission rate. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

vulnerability. For example, a well-known vulnerability with enormous potential for exploitation might be assigned a high threat score. Meanwhile, less severe vulnerabilities may be assigned a lower score. The higher the FOR rate, the less effective an optimization strategy is in optimizing energy use. It is important to note that FORs depend on the optimization strategies employed and the criteria used to identify peak loads. It can be monitored by tracking the FOR, and optimization strategies can be improved. Table 6 expresses the evaluation of the threat score between the existing and proposed models.

TABLE 5 Evaluation of prevalence threshold (in %).

Inputs	EEC	GA	QARP	MQRP	EOF
100	69.32	72.50	77.25	71.57	88.40
200	69.65	74.00	77.84	73.44	89.44
300	70.99	75.11	78.82	74.27	89.57
400	72.13	75.49	80.03	75.18	90.53
500	73.18	76.50	81.17	76.10	90.10
600	73.89	77.43	82.28	77.43	91.34
700	75.19	78.43	82.98	78.30	91.45

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

Figure 8 shows the evaluation of the threat score. In an estimation phase, EEC reached 70.33%, GA obtained 59.20%, QARP reached 76.79%, and MQRP obtained 66.65% sensitivity. The proposed EOF obtained 91.27% sensitivity.

5.6 | Convergence of performance

It is designed to help administrators prioritize their resources for mitigation, as the ranking indicates which vulnerabilities should receive the most excellent attention. For example, a

TABLE 6 Evaluation of threat score (in %).

Inputs	EEC	GA	QARP	MQRP	EOF
100	67.86	65.06	66.52	76.79	91.05
200	66.20	59.20	73.36	71.38	91.15
300	65.75	60.34	74.65	69.89	91.22
400	70.33	59.20	76.79	66.65	91.27
500	70.83	58.32	75.22	67.37	91.31
600	70.67	57.12	73.60	67.50	91.34
700	69.93	55.47	71.80	66.23	91.34

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

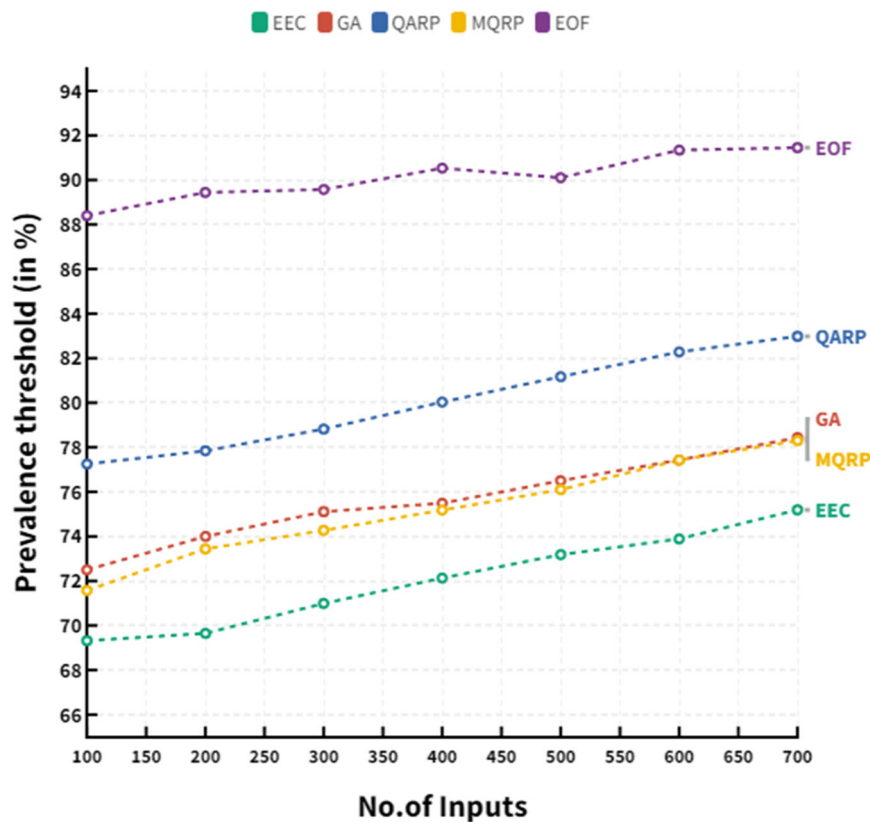
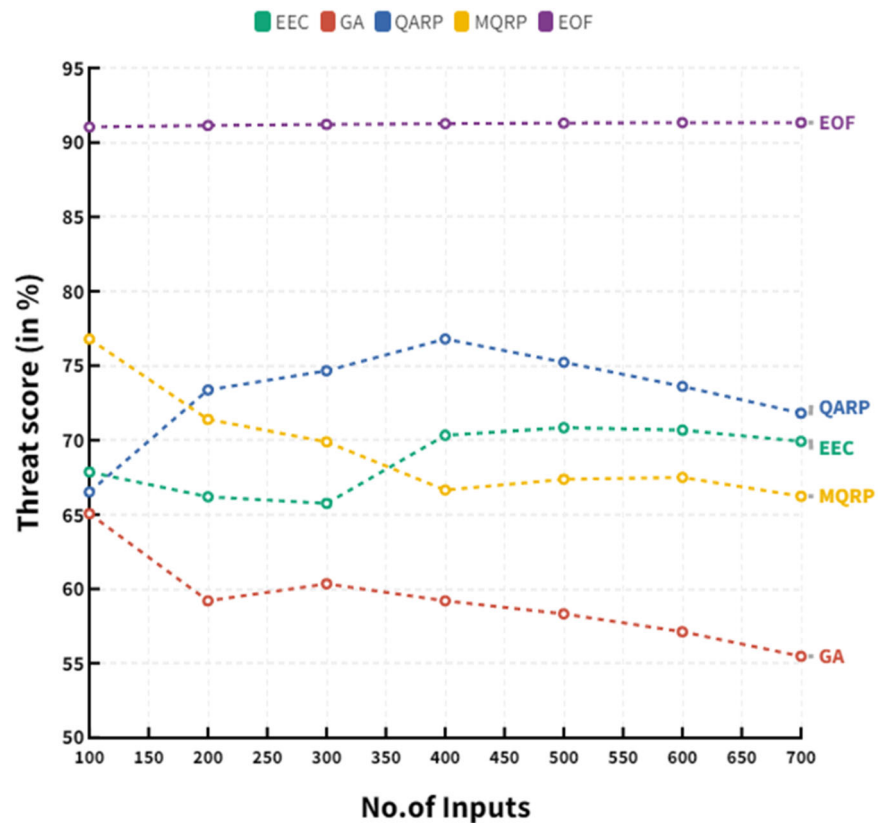


FIGURE 7 Evaluation of prevalence threshold. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

FIGURE 8 Evaluation of threat score. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.



system with three vulnerabilities ranked as “critical,” “high,” and “moderate” might receive a higher score than one with the same vulnerabilities rated as “low.” The threat score is integral to the overall risk assessment process and can help administrators identify which areas require the most attention. It is important to note that threat scores do not evaluate the likelihood or impact of potential attacks and should not be used as such. Table 7 expresses the evaluation of overall performance between the existing and proposed models.

Figure 9 shows the evaluation of overall performance. In a peak computational range, the proposed EOF reached 96.93% sensitivity, 91.36% FDR, 11.28% FOR, 90.12% prevalence threshold, and 91.24% threat score. Meanwhile, the existing EEC reached 59.86% sensitivity, 69.58% FDR, 38.58% FOR, 72.05% prevalence threshold, and 68.80% threat score. GA reached 53.92% sensitivity, 64.12% FDR, 38.48% FOR, 75.64% prevalence threshold, and 59.24% threat score. QARP reached 86.69% sensitivity, 80.12% FDR, 47.64% FOR, 80.05% prevalence threshold, and 73.13% threat score. MQRP reached 78.19% sensitivity, 65.89% FDR, 26.39% FOR, 75.18% prevalence threshold, and 69.40% threat score. Comparative analysis is essential to energy optimization in Industry 4.0 because it allows for a detailed comparison between production and energy-related information. By comparing variables, such as energy consumption,

TABLE 7 Evaluation of overall performance (in %).

Parameters	EEC	GA	QARP	MQRP	EOF
Sensitivity (S)	59.86	53.92	86.69	78.19	96.93
False discovery rate (FDR)	69.58	64.12	80.12	65.89	91.36
False omission rate (FOR)	38.58	38.48	47.64	26.39	11.28
Prevalence threshold (P_{th})	72.05	75.64	80.05	75.18	90.12
Threat score (TS)	68.80	59.24	73.13	69.40	91.24

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

production process parameters, and equipment efficiency, engineers and managers can identify areas of improvement and pinpoint potential cost savings. This analysis can be used to identify areas of inefficiency and target potential new sources of energy production. By comparing different energies, such as wind and solar, the analysis can support the decision-making process for energy investments. The comparative analysis can also be used to identify the advantages and disadvantages of various energy sources, helping managers better understand energy availability and its costs. It can be used to

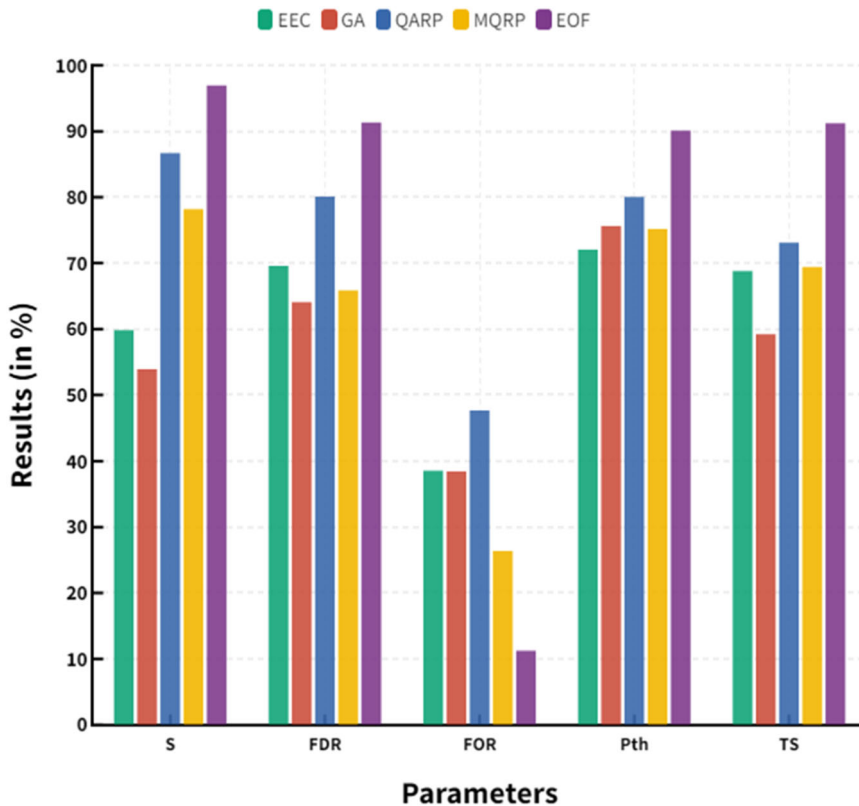


FIGURE 9 Evaluation of overall performance. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

compare past energy behaviors with current practices to identify any discrepancies or areas for improvement. It can help to inform decisions about energy optimization and conservation strategies.

6 | DISCUSSION

Sensor nodes in Industry 4.0 are designed to conserve energy by using low-power technologies and intelligent power management systems. These systems use a combination of protocols, such as duty cycling, mesh networking, and scheduling algorithms, to maximize energy efficiency. They are designed to reduce power consumption to extend battery life, enabling devices to run longer on a single charge. It is extremely low-power sleep states that help conserve energy in idle periods, and adaptive radio power settings can be used to minimize radio transmission power where appropriate. It ensures that sensing nodes are only transmitting and receiving data when necessary.

6.1 | Analysis of energy conservation

Sensitivity is a measure of how accurately a sensor node can detect changes in its environment. By increasing the sensitivity of a sensor node, its accuracy and energy

conservation can be improved. A higher sensitivity of a sensor node results in faster and more accurate detection of changes in the environment, allowing for more precise control of industrial processes and energy consumption. The use of sensitivity can help reduce energy consumption by quickly and accurately detecting changes in the environment. It can be extremely beneficial in improving the efficiency and performance of industrial processes.

FDR is used to reduce energy consumption by accurately identifying and discarding packets that are deemed redundant or of no value. By utilizing the FDR, sensor nodes can work much more efficiently since they are only sending the important data needed by the network and not wasting time or energy on unnecessary data. It helps to reduce the amount of energy used overall, improving the performance of the sensor nodes and thus providing a more efficient and reliable industrial IoT environment.

FOR is used in conjunction with an energy-efficient algorithm to compute the ratio of missed detections to successful detections. It helps to determine the reliability and accuracy of an algorithm in sensing or identifying objects in Industrial 4.0. By computing the FOR, the system can increase the energy efficiency of the sensors, as well as improve the performance of the sensors to determine and detect objects in real-time accurately. It leads to better energy conservation and increased efficiency of the sensor nodes, which are important in Industry 4.0.

The prevalence threshold calculation helps to increase the energy conservation of sensor nodes by taking into account the nodes' historical performance data to determine at which point in time they can be activated for further energy savings with only a minimal loss in performance. The prevalence threshold helps to identify when the node should be activated and how long it should remain activated to maximize energy savings and system performance. As a result, Industry 4.0 sensor nodes can operate longer and more efficiently, maximizing their energy efficiency and performance.

The computation of the threat score helps to increase energy conservation in Industry 4.0 by providing a comprehensive risk assessment, identifying areas of vulnerability, tracking malicious actors and activities, and reducing energy consumption in the sensor nodes. It is done by reducing unnecessary data access, engaging in real-time system scans, and making local decisions about individual node operations. Threat scoring helps to identify malicious activities faster, which minimizes power consumption. By understanding the threats, Industry 4.0 can make more informed decisions about how to optimize energy conservation in sensor nodes, reducing energy wastage and improving performance. Table 8 shows the comparison of energy conservation in various modes of sensor nodes.

Figure 10 shows the comparison of energy conservation in various modes of sensor nodes. In Sleep mode, the proposed EOF reached 95.53% energy conservation. It is 25.17% better than EEC, 12.28% better than GA, 6.19% better than QARP, and 19.48% better than MQRP. In Idle mode, the proposed EOF reached 95.37% energy conservation. It is 26.31% better than EEC, 13.12% better than GA, 6.73% better than QARP, and 20.4% better than MQRP. In Active mode, the proposed EOF reached 95.21% energy conservation. It is 27.45% better than EEC, 13.96% better than GA, 7.27% better than QARP, and 21.32% better than MQRP. The following are the reasons for the proposed model to obtain maximum energy conservation:

- **Sensitivity:** This is an attribute of the proposed model that helps to detect and classify potential malicious

TABLE 8 Comparison of energy conservation (in %).

Sensor mode	EEC	GA	QARP	MQRP	EOF
Sleep mode	70.36	83.25	89.34	76.05	95.53
Idle mode	69.06	82.25	88.64	74.97	95.37
Active mode	67.76	81.25	87.94	73.89	95.21

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

threats accurately. It measures the probability of accurately detecting an intrusion, making it possible to control for false positive and false negative alarms.

- **FDR:** This measures the rate at which false alarms are detected, providing information about the accuracy of the proposed model. By controlling for false positives, this attribute helps improve overall energy conservation.
- **FOR:** This measures the rate at which true alarms are missed, providing another measure of the accuracy of the proposed model. By controlling for false negatives, this attribute helps eliminate security threats that may otherwise not be detected.
- **Prevalence threshold:** This is the level of data activity that indicates the presence of a potential malicious threat. It helps to identify such threats before they are able to cause serious damage, making it possible to intervene quickly and prevent malicious activity.
- **Threat score:** This attribute helps to determine the overall severity of a potential threat. It is based on a range of factors, such as the prevalence of the threat, its history, and its severity. By weighing these factors, the proposed model helps to identify and prioritize threats that pose the greatest risk to overall energy conservation.

6.2 | Analysis of energy harvesting

The computation of sensitivity enables the IoT nodes to detect changes in energy consumption patterns and optimize the efficiency of such nodes. It increases the harvesting of energy, which enhances the performance of the nodes and makes them ready for applications. The computation of sensitivity helps in improving the accuracy of predictions with regard to the energy requirements of the nodes. It, in turn, leads to a more consistent source of energy and helps in reducing the associated expenses.

FDR helps to identify which correlations are more likely to be real and more likely to yield meaningful insights. By identifying meaningful correlations between sensor data and energy harvesting, FDR can increase efficiency and effectiveness in how much energy is harvested. It can allow for better-informed decisions on energy efficiency strategies, like how to increase energy harvesting to enhance the performance of sensor nodes.

FOR is a measure of the accuracy of a sensor system that describes the probability of the system not detecting a certain event despite the event occurring. It is especially important, as data generated by sensor nodes is integral to the effective operation of the system. By accurately calculating the FOR, sensor nodes can be

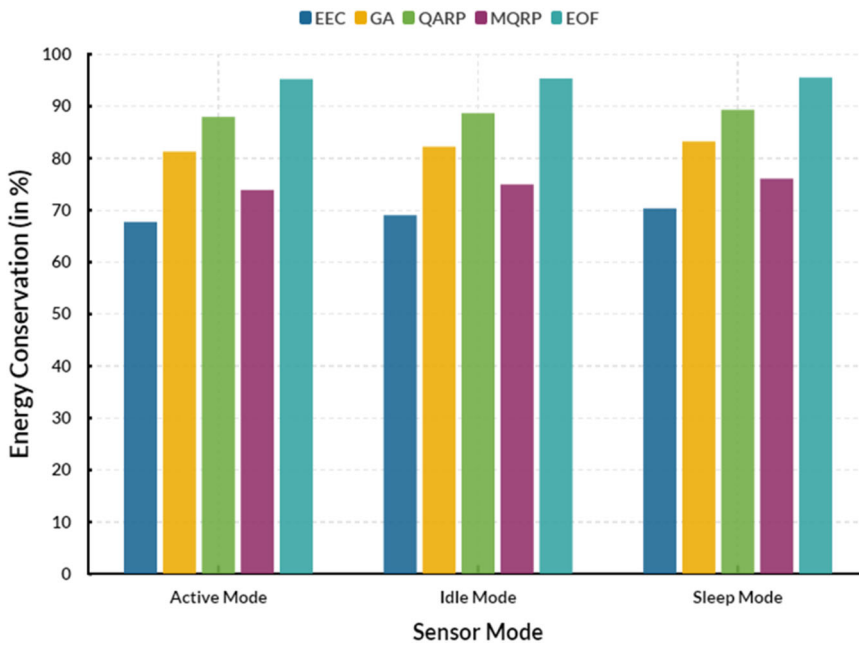


FIGURE 10 energy conservation in various modes of sensor nodes. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

configured to optimally capture energy, allowing them to be powered with less energy, thereby improving their performance and making them more energy efficient.

The computation of the prevalence threshold rate helps to increase the energy harvesting to enhance the performance of sensor nodes by providing a mechanism for deciding when to switch on or off certain sensors depending on the expected signal prevalence. It calculates the amount of energy needed to maintain minimum signal strength at any given node, which helps the node determine when to switch off certain sensors if the signal is not of sufficient strength. It helps to reduce the overall energy consumption of the sensor nodes while still ensuring that sufficient signal strength is maintained for data collection purposes.

The computation of the threat score rate is used to measure the cyber threats and security risks associated with sensor nodes. By determining the threats in an environment, it becomes possible to increase the energy harvesting of the devices and ensure their security, leading to improved performance and functionality of the sensor nodes. This rate can also be used to better prepare for future security threats and to develop more secure energy harvesting mechanisms. Table 9 shows the comparison of energy harvesting in various modes of sensor nodes.

Figure 11 shows the comparison of energy harvesting in various modes of sensor nodes. In Sleep mode, the proposed EOF reached 95.05% energy harvesting. It is 28.62% better than EEC, 14.8% better than GA, 7.81% better than QARP, and 22.24% better than MQRP. In Idle mode, the proposed EOF reached 94.89% energy harvesting. It is 29.73% better than EEC, 15.64% better

TABLE 9 Comparison of energy harvesting (in %).

Sensor mode	EEC	GA	QARP	MQRP	EOF
Sleep mode	66.46	80.25	87.24	72.81	95.05
Idle mode	65.16	79.25	86.54	71.73	94.89
Active mode	63.86	78.25	85.84	70.65	94.73

Abbreviations: EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

than GA, 8.35% better than QARP, and 23.16% better than MQRP. In Active mode, the proposed EOF reached 94.73% energy harvesting. It is 30.87% better than EEC, 16.48% better than GA, 8.89% better than QARP, and 24.08% better than MQRP. The following are the reasons for the proposed model to obtain maximum energy harvesting:

- **Sensitivity:** The proposed model uses sensitivity to adjust the power harvesting parameters to maximize the energy harvesting capabilities. Sensitivity allows the model to adjust the precision of the harvesting parameters to optimize energy conversion efficiency.
- **FDR:** The proposed model uses an FDR to guarantee that no false positives or false negatives occur during the harvest. It helps optimize the energy harvest while avoiding waste of resources.
- **FOR:** The proposed model uses a FOR to ensure that no potential energy sources are missed during the harvesting process. It helps reduce waste of energy and increase overall efficiency.

FIGURE 11 Energy harvesting in various modes of sensor nodes. EEC, energy-efficiency clustering; EOF, energy optimization framework; GA, genetic algorithm; MQRP, mobile sinks-based QoS-aware data gathering protocol; QARP, QoS-aware routing protocol.

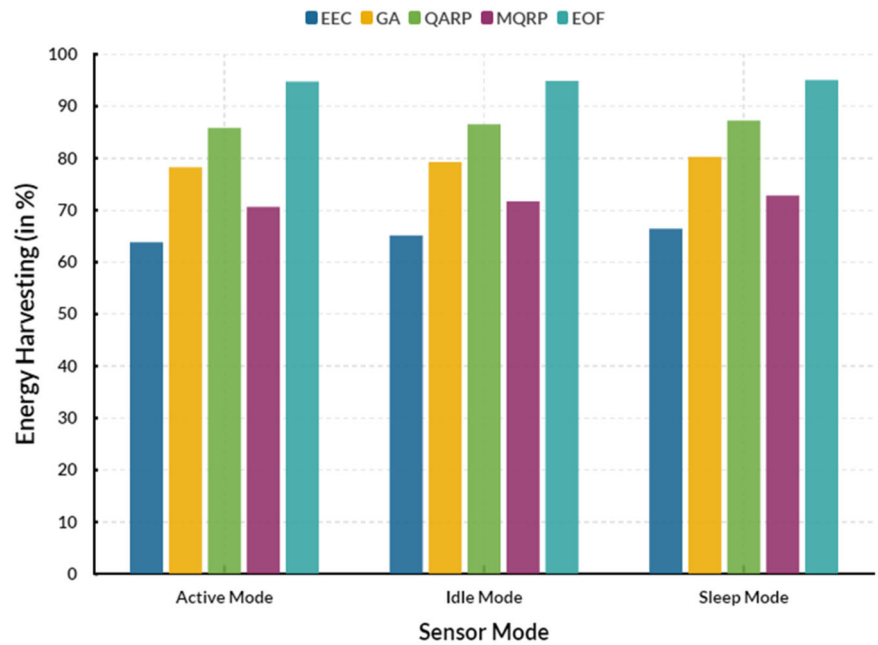


TABLE 10 Comprehensive performance analysis.

Authors	Year	Sensitivity (%)	Energy conservation (%)	Energy harvesting (%)
Wang et al. ²⁹	2022	95.46	91.12	89.47
Haque et al. ³⁰	2021	92.19	89.84	91.57
Yan et al. ³¹	2017	90.36	89.68	90.22
Devesh et al. ³²	2020	91.43	92.36	94.68
Wan et al. ³³	2016	88.88	91.64	85.55
Leonardi et al. ³⁴	2018	87.48	91.96	86.43
Kumar et al. ³⁵	2019	86.09	92.32	87.91
Logeshwaran et al. ³⁶	2023	84.70	92.78	91.25
Preuveneers et al. ³⁷	2017	83.31	93.64	89.68
Faheem et al. ³⁸	2021	81.92	93.42	85.97
Blanco-Novoa et al. ³⁹	2018	90.52	93.76	92.65
Sherazi et al. ⁴⁰	2018	89.13	94.12	90.78
Souza et al. ⁴¹	2021	87.74	94.48	89.64
Mistarihi et al. ⁴²	2023	86.35	94.84	88.54
Alfawaz et al. ⁴³	2023	94.70	88.45	91.36
Hammad et al. ⁴⁴	2023	93.31	90.56	90.83
Lilhore et al. ⁴⁵	2023	91.92	91.68	84.22
Proposed (P)	2023	96.93	95.53	95.05

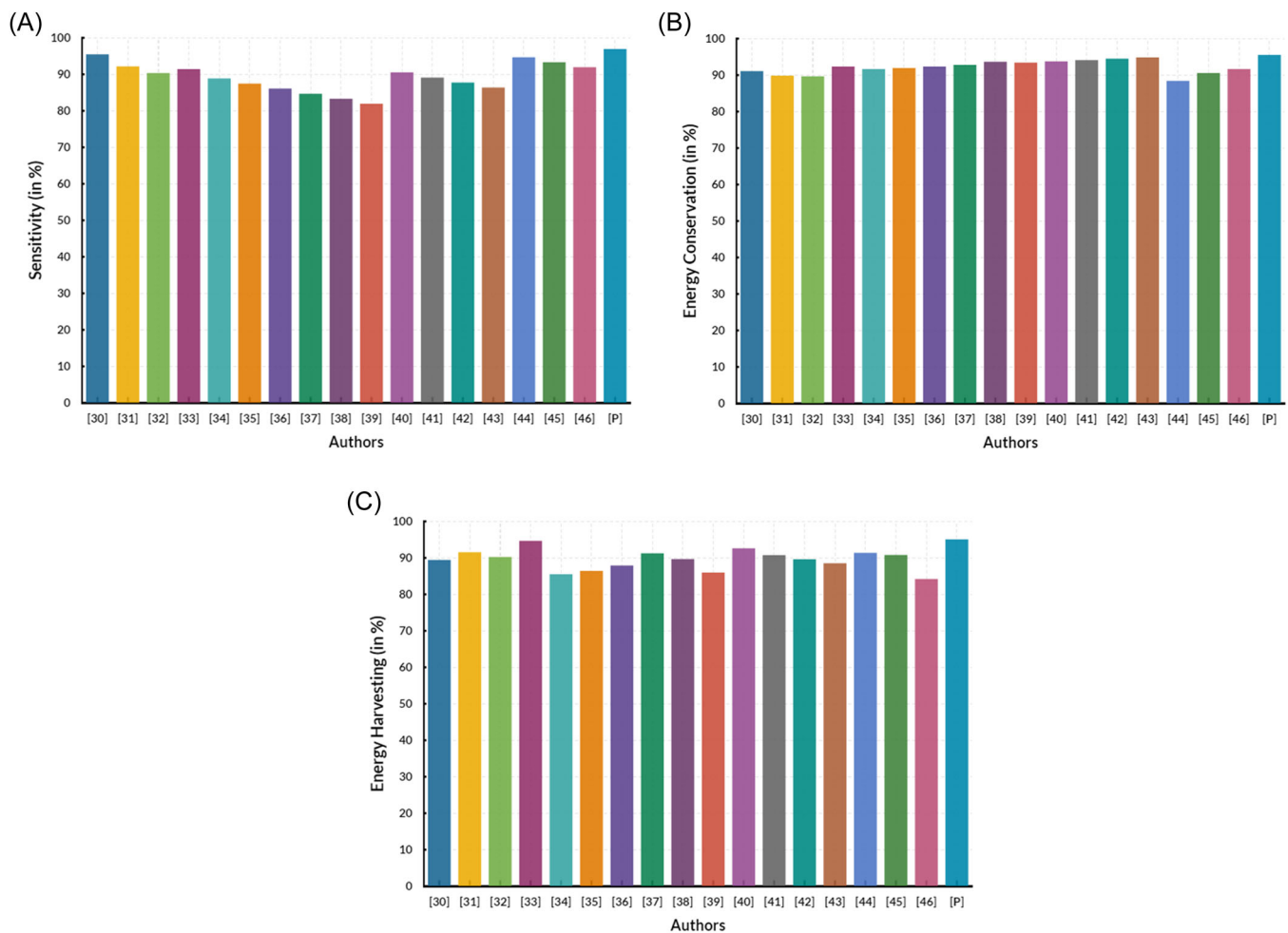


FIGURE 12 (A) Performance analysis of sensitivity. (B) Performance analysis of energy conservation. (C) Performance analysis of energy harvesting.

- Prevalence threshold: The proposed model uses a prevalence threshold to reduce the false positive rate during the energy harvesting process. It helps optimize energy harvesting efficiency by focusing energy acquisition on the most reliable sources.
- Threat score: The proposed model calculates a threat score to maintain security and integrity during the harvesting process. It helps ensure the highest possible efficiency and safety during the energy harvesting process.

6.3 | Quantitative analysis

The energy harvesting performance of sensor nodes aims at improving the sleep/wake-up cycles to provide power and reduce energy consumption without compromising performance or reliability. It can be achieved by harvesting energy from any available renewable sources like solar, wind, and thermal energy. Table 10 shows the comprehensive performance analysis.

Figure 12 shows the overall performance analysis. (a) Sensitivity, (b) energy conservation, and (c) energy harvesting. The battery life of the sensor node can be extended by optimizing power consumption technologies like RF harvesting and power optimization techniques, such as duty-cycle modulation and dynamic power control. The energy harvesting performance of sensor nodes can also be improved by using low-power hardware design techniques, such as power-aware system design, optimized algorithms, and software optimization. System design can reduce power consumption by improving the system architecture and selecting the most appropriate components. Optimized algorithms can be used to improve the efficiency of the algorithms used by the system. The energy harvesting performance of sensor nodes is important for both the cost-efficiency and reliability of Industry 4.0 IoT systems. By optimizing the power consumption, the energy budget can be reduced, and the battery life of sensor nodes can be extended.

The use of machine learning algorithms in WSNs indeed comes with an additional energy cost. To effectively use ML algorithms for energy management in WSNs, a number of parameters should be taken into account:

- It is important to consider the type of ML algorithm used, as some algorithms are more suitable for certain tasks than others. For example, supervised learning algorithms are generally used for classification tasks, while unsupervised learning algorithms are used for clustering tasks.
- The number of parameters used by the ML algorithm must be carefully controlled to avoid overfitting and ensure efficient energy management.
- The size of the training set should be taken into account, as larger training datasets will require more energy for the ML algorithm to process. To effectively use ML algorithms for energy management in WSNs with very low energy scales, specialized algorithms that are capable of processing a small amount of data with acceptable accuracy must be developed. Examples of such algorithms include batch-learning algorithms and reduced-memory algorithms.
- These specialized algorithms should have minimal computational requirements and lead to a reduction in the overall energy consumption of the network.

7 | CONCLUSION

It is an optimal solution for controlling energy costs, reducing operational costs, and improving sustainability initiatives. This framework helps industries to optimize their energy use more efficiently. It starts with collecting and analyzing energy data to identify energy-saving opportunities, enabling companies to discover the most optimal energy management strategy. It will improve overall operations, enhance product quality, reduce energy wastage, and increase cost savings. The framework helps companies leverage the latest technologies, like machine learning and AI, to predict energy behavior and optimize energy usage. It ensures optimal energy efficiency and drives industries toward sustainable growth. The EOF reached 96.93% sensitivity, 91.36% FDR, 11.28% FOR, 90.12% prevalence threshold, and 91.24% threat score. It is a sophisticated system that promises more intelligent, more efficient energy usage. This framework utilizes the IoT, advanced analytics, and AI to create a complete optimization system. It focuses on reducing energy consumption, minimizing energy costs, and increasing efficiency. With the advent of Industry 4.0, this framework offers potential for the future of energy management. Applying this framework across industries can have a

tremendous impact on energy consumption. The framework can increase efficiency and reduce waste from factories and machine shops to manufacturing and commercial buildings. The energy savings in these industries can be impressive, leading to reduced energy costs that can be passed on directly to customers. The proposed framework holds promise in developing renewable and clean energy sources, as it can monitor and optimize renewable energy sources, such as solar and wind energy. The framework can prioritize and allocate resources to reduce costs and emissions by tracking and analyzing energy usage. The proposed model has many potential applications and future scope. From reducing energy costs to developing renewable and clean energy sources, it holds great promise for creating a more efficient, sustainable, and cost-effective energy future.

AUTHOR CONTRIBUTIONS

Sangeetha R: Conceptualization; methodology; software; visualization; writing—original draft. **Jaganathan Logeshwaran:** Formal analysis; resources; writing—review and editing. **Raju Kannadasan:** Data curation; validation. **Muhammad Faheem:** Data curation; investigation; software; validation; writing—review and editing. **Dhanasekar Ravikumar:** Investigation; data curation; supervision; validation.

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DATA AVAILABILITY STATEMENT

Data will be available on request.

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REFERENCES

1. Alrashidi M, Nasri N, Khediri S, Kachouri A. Energy-efficiency clustering and data collection for wireless sensor networks in industry 4.0. *J Ambient Intell Humanized Comput*. 2020;8:1-8.
2. Kanoun O, Khriji S, Naifar S, et al. Prospects of wireless energy-aware sensors for smart factories in the industry 4.0 era. *Electronics*. 2021;10(23):2929.
3. Avinash Khatri KC, Shah KB, Logeshwaran J, Shrestha A. Genetic algorithm based techno-economic optimization of an isolated hybrid energy system. *ICTACT J Microelectron*. 2023;8(4):1447-1450.

4. Catenazzo D, O'Flynn B, Walsh M. On the use of wireless sensor networks in preventative maintenance for industry 4.0. 2018 12th International Conference on Sensing Technology (ICST). IEEE. 2018:256-262.
5. Kathiriya H, Pandya A, Dubay V, Bavarva A. State of art: energy efficient protocols for self-powered wireless sensor network in IIoT to support industry 4.0. 2020 8th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). IEEE. 2020:1311-1314.
6. Ferreira P, Miranda RN, Cruz PM, Mendonça HS. Multi-protocol LoRaWAN/Wi-Fi sensor node performance assessment for industry 4.0 energy monitoring. 2019 IEEE-APS Topical Conference on Antennas and Propagation in Wireless Communications (APWC). IEEE. 2019:403-407.
7. Li X, Li D, Wan J, Vasilakos AV, Lai CF, Wang S. A review of industrial wireless networks in the context of industry 4.0. *Wireless Networks*. 2017;23:23-41.
8. Faheem M, Gungor VC. Energy efficient and QoS-aware routing protocol for wireless sensor network-based smart grid applications in the context of industry 4.0. *Appl Soft Comput*. 2018;68:910-922.
9. Faheem M, Gungor VC. MQRP: mobile sinks-based QoS-aware data gathering protocol for wireless sensor networks-based smart grid applications in the context of industry 4.0-based on Internet of things. *Future Generation Comput Syst*. 2018;82:358-374.
10. Huang Z, Kim J, Sadri A, Doweiy S, Dargusch MS. Industry 4.0: development of a multi-agent system for dynamic value stream mapping in SMEs. *J Manufact Syst*. 2019;52:1-12.
11. Raja S, Logeshwaran J, Venkatasubramanian S, et al. OCHSA: designing energy-efficient lifetime-aware leisure degree adaptive routing protocol with optimal cluster head selection for 5G communication network disaster management. *Sci Programm*. 2022;2022:1-11.
12. Voges S, Becker KF, Schütze D, et al. Highly miniaturized integrated sensor nodes for Industry 4.0. International Symposium on Microelectronics. International Microelectronics Assembly and Packaging Society. Vol 2019. 2019:000415-000422.
13. Angelopoulos A, Michailidis ET, Nomikos N, et al. Tackling faults in the industry 4.0 era—a survey of machine-learning solutions and key aspects. *Sensors*. 2019;20(1):109.
14. Raza S, Faheem M, Guenes M. Industrial wireless sensor and actuator networks in industry 4.0: exploring requirements, protocols, and challenges—a MAC survey. *Int J Commun Syst*. 2019;32(15):e4074.
15. Faheem M, Butt RA. Big datasets of optical-wireless cyber-physical systems for optimizing manufacturing services in the Internet of things-enabled industry 4.0. *Data Brief*. 2022;42:108026.
16. Alsamhi SH, Shvetsov AV, Kumar S, et al. Computing in the sky: A survey on intelligent ubiquitous computing for UAV-assisted 6G networks and industry 4.0/5.0. *Drones*. 2022;6(7):177.
17. Sahal R, Alsamhi SH, Breslin JG, Ali MI. Industry 4.0 towards forestry 4.0: fire detection use case. *Sensors*. 2021;21(3):694.
18. Sahal R, Alsamhi SH, Breslin JG, Brown KN, Ali MI. Digital twins collaboration for automatic erratic operational data detection in industry 4.0. *Appl Sci*. 2021;11(7):3186.
19. Srivastava R, Alsamhi SH, Murray N, Devine D. Shape memory alloy-based wearables: a review, and conceptual frameworks on HCI and HRI in industry 4.0. *Sensors*. 2022;22(18):6802.
20. Qi N, Dai K, Wang X, You Z. Optimization for piezoelectric energy harvesters with self-coupled structure: A double kill in bandwidth and power. *Nano Energy*. 2022;102:107602.
21. Qi N, Yin Y, Dai K, Wu C, Wang X, You Z. Comprehensive optimized hybrid energy storage system for long-life solar-powered wireless sensor network nodes. *Appl Energy*. 2021;290:116780.
22. Qi N, Dai K, Wang X, You Z. Adaptive capacitor charging circuit with simplified configuration for efficient piezoelectric energy harvesting. *IEEE Trans Power Electron*. 2022;37(9):10267-10280.
23. Liu X, Qi N, Dai K, et al. Sponge supercapacitor rule-based energy management strategy for wireless sensor nodes optimized by using dynamic programming algorithm. *Energy*. 2022;239:122368.
24. Dai K, Zhang C, Li Q, Huang X, Zhang H. An adaptive energy management strategy for simultaneous long life and high wake-up success rate of wireless sensor network nodes. *Energy Technol*. 2021;9(10):2100522.
25. Henao-Hernández I, Solano-Charris EL, Muñoz-Villamizar A, Santos J, Henríquez-Machado R. Control and monitoring for sustainable manufacturing in the industry 4.0: a literature review. *IFAC-PapersOnLine*. 2019;52(10):195-200.
26. Lin CC, Deng DJ, Chen ZY, Chen KC. Key design of driving industry 4.0: joint energy-efficient deployment and scheduling in group-based industrial wireless sensor networks. *IEEE Commun Magazine*. 2016;54(10):46-52.
27. Alhayani B, Kwekha-Rashid AS, Mahajan HB, et al. 5G standards for the Industry 4.0 enabled communication systems using artificial intelligence: perspective of smart healthcare system. *Appl Nanosci*. 2023;13:1807-1817.
28. Sherazi HHR, Grieco LA, Imran MA, Boggia G. Energy-efficient LoRaWAN for Industry 4.0 applications. *IEEE Trans Industr Inform*. 2021;17(2):891-902.
29. Wang C, Wang D, Xu G, He D. Efficient privacy-preserving user authentication scheme with forward secrecy for industry 4.0. *science China. Inf Sci*. 2022;65(1):112301.
30. Haque ME, Baroudi U. Ambient self-powered cluster-based wireless sensor networks for industry 4.0 applications. *Soft Comput*. 2021;25:1859-1884.
31. Yan J, Meng Y, Lu L, Li L. Industrial big data in an industry 4.0 environment: challenges, schemes, and applications for predictive maintenance. *IEEE Access*. 2017;5:23484-23491.
32. Devesh M, Kant AK, Suchit YR, Tanuja P, Kumar SN. Fruition of CPS and IoT in context of Industry 4.0. Intelligent Communication, Control and Devices: Proceedings of ICICCD 2018. Springer Singapore. 2020:367-375.
33. Wan J, Tang S, Shu Z, et al. Software-defined industrial Internet of things in the context of industry 4.0. *IEEE Sens J*. 2016;16(20):1.
34. Leonardi L, Battaglia F, Patti G, Bello LL. Industrial LoRa: a novel medium access strategy for LoRa in industry 4.0 applications. *IECON 2018—44th Annual Conference of the IEEE Industrial Electronics Society*. IEEE. 2018:4141-4146.
35. Kumar N, Kumar J. Efficiency 4.0 for Industry 4.0. *human. Technology*. 2019;15(1):55.

36. Logeshwaran J, Kiruthiga T, Kannadasan R, et al. Smart Load-Based resource optimization model to enhance the performance of device-to-device communication in 5G-WPAN. *Electronics*. 2023;12(8):1821.
37. Preuveneers D, Ilie-Zudor E. The intelligent industry of the future: a survey on emerging trends, research challenges and opportunities in Industry 4.0. *J Ambient Intell Smart Environ*. 2017;9(3):287-298.
38. Faheem M, Butt RA, Ali R, Raza B, Ngadi MA, Gungor VC. CBI4. 0: a cross-layer approach for big data gathering for active monitoring and maintenance in the manufacturing industry 4.0. *J Industr Inform Integration*. 2021;24:100236.
39. Blanco-Novoa O, Fernandez-Carames TM, Fraga-Lamas P, Vilar-Montesinos MA. A practical evaluation of commercial industrial augmented reality systems in an industry 4.0 shipyard. *IEEE Access*. 2018;6:8201-8218.
40. Sherazi HHR, Imran MA, Boggia G, Grieco LA. Energy harvesting in LoRaWAN: a cost analysis for the industry 4.0. *IEEE Commun Lett*. 2018;22(11):2358-2361.
41. Souza LC, Neto ER, Lima ES, Junior ACS. Optically-powered wireless sensor nodes towards industrial Internet of Things. *Sensors*. 2021;22(1):57.
42. Mistarihi MZ, Bany Salameh HA, Alsaadi MA, Beyca OF, Heilat L, Al-Shobaki R. Energy-efficient bi-objective optimization based on the moth-flame algorithm for cluster head selection in a wireless sensor network. *Processes*. 2023;11(2):534.
43. Alfawaz O, Osamy W, Saad M, Khedr AM. Modified rat swarm optimization based localization algorithm for wireless sensor networks. *Wireless Personal Commun*. 2023;130(3):1617-1637.
44. Hammad M, Jillani RM, Ullah S, et al. Security framework for network-based manufacturing systems with personalized customization: an industry 4.0 approach. *Sensors*. 2023;23(17):7555.
45. Lilhore UK, Manoharan P, Simaiya S, et al. HIDM: hybrid intrusion detection model for industry 4.0 networks using an optimized CNN-LSTM with transfer learning. *Sensors*. 2023;23(18):7856.
46. Kaggle. Sensor Fault Detection Data. <https://www.kaggle.com/datasets/arashnic/sensor-fault-detection-data>

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