

A Machine Learning-Based Framework for Communication Failure Detection in Directional Industrial IoT Networks

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Abstract—Industrial systems require the transport of large amounts of data, including high-definition video and sensor data, across IIoT equipment. This broadcast usually has strict time limits. Millimeter-wave (mmWave) frequencies at 28 and 60 GHz can quickly transfer data to meet IIoT requirements. This is done with mmWave frequencies. Directional antennas are crucial in the millimeter wave (mmWave) frequency range due to its limited wavelength. Directed connections are fragile and prone to problems like deafness, which occurs when a communication node cannot receive signals from simultaneously sending nodes. This study uses machine learning to treat hearing impairment in millimeter wave (mmWave) device-to-device (D2D) communication. The purpose of this research is to solve the problem. The researchers intend to build a reliable connection and recognize communication failures by using the methods in this publication. The suggested methodology categorizes network problems, specifically deafness and interference, by examining IIoT device status indicators. We also suggest using ML-DMAC to improve data throughput and reduce communication downtime in Device-to-Device (D2D) networks.

Index Terms— Industrial Internet of Things, Communication, Machine learning, Directional MAC.

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I. INTRODUCTION

As a result of the incorporation of digital technology and physical machinery into the Industrial Internet of Things (IIoT), the processes that are used in industry are experiencing a metamorphosis. The implementation of this integration is resulting in enhancements to both the operational efficiency and the overall optimization. When faced with situations like these, it is of the utmost necessity to convey massive amounts of data in an efficient or effective manner. This encompasses a wide range of information, including video feeds with a high resolution and massive amounts of signal data from sensors. The significance of this is of the utmost importance for a wide variety of applications, including, but not limited to, quality control, process monitoring, and predictive maintenance, amongst others. When it comes to meeting the strict criteria of applications that are part of the Industrial Internet of Things (IIoT), sophisticated communication technologies play a vital role. The ability to transport data at fast rates, with little latency, and with consistent performance are all characteristics of these technologies [1]. When it comes to addressing the bandwidth requirements of Industrial Internet of Things (IIoT) applications, the exploitation of millimeter-wave (mmWave) communication presents a solution that is particularly successful. Because of this, millimeter-wave communication, which is also referred to as mm Wave communication, makes use of frequencies of 28 and 60 GHz. This results in greatly enhanced data transfer speeds in compared to the frequencies that are typically used for microwave communication. Communication by microwaves (mmWave), on the other hand, is fraught with considerable challenges, particularly in industrial settings where dependability is of the utmost critical importance. The limited wavelength of millimeter wave (mmWave) communications presents a significant obstacle when it comes to the incorporation of directional antennas into the grid. Notwithstanding the fact that they offer advantages such as increased spatial reuse and an overall reduced level of interference, directional antennas are prone to difficulties like as signal attenuation. This is the case despite the fact that they give benefits. Deafness is a circumstance in which a receiving node is unable to receive signals from other transmitting nodes due to misalignment or obstruction [2]. The term deafness alludes to this condition.

This state of affairs is commonly referred to as "deafness." In order to construct communication that is not only dependable but also as efficient as it can possibly be, it is absolutely vital to take into account the problem of hearing impairment within the context of specialized industrial Internet of Things (IoT) networks. There are inherent limitations to the conventional approaches that are utilized in the process of mitigating the consequences of deafness. These approaches include beamforming and channel prediction algorithms. With regard to dynamic industrial settings, which are defined by changeable operational conditions, this is especially true. As a result, it is of the utmost importance to build unique solutions that are capable of responding to the ever-changing conditions of the network and being able to effectively notice and treat any interruptions in communication [3].

This study proposes a unique machine learning approach for the identification of communication failures in directed industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) frequency band. The research was carried out by the authors of this study. Following the conclusions of this inquiry, the strategy was established in accordance with those findings. For the purpose of analyzing the performance indicators of Industrial Internet of Things (IIoT) devices and classifying network issues as either interference or perceptual impairment, the methodology that has been recommended makes use of techniques that are associated with machine learning. The method that has been created makes it possible to execute interventions that are both early and targeted in order to reduce the impact that would otherwise be had on the performance of the network [4]. The correct identification of the particular kind of communication breakdown that has taken place is the means by which this has been accomplished. Additionally, we provide ML-DMAC, which is a Medium Access Control (MAC) protocol that includes machine learning methodologies in order to improve device-to-device (D2D) network communication. This protocol falls under the category of Medium Access Control. Within the scope of this approach, one of the objectives is to reduce the length of time that an individual is affected by auditory impairment while simultaneously enhancing the effectiveness of processing speed. The ML-DMAC technique makes use of data obtained from a diagnostic system that is meant to discover communication problems [5]. This allows the technique to alter MAC parameters and boost the efficiency of real-time communication hence improving the effectiveness of the connection.

The problem of auditory impairment is illustrated in Figure 1, which displays the situation in the context of direct connection between devices that are a part of the Industrial Internet of Things (IIoTD). As can be seen in Figure 1, the communication between IIoTDs X and Y strictly prohibits the utilization of antennas that are not the designated communication antenna. No matter what the conditions are, this is not permitted. Therefore, the DRTS frames that originate from IIoTDs A and B are unable to successfully arrive at the destinations that these frames are meant for. This is because of the fact that this is the case.

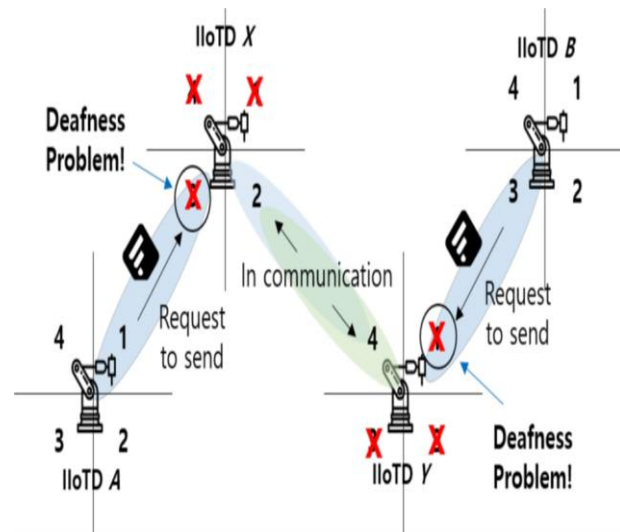


Fig. 1. Deafness difficulty in D2D communication

II. RELATED WORK

When it comes to the Internet of Things (IoT) networks that are used in industrial settings, a considerable amount of academic study has been devoted to the investigation of the problems that are related with millimeter wave (mmWave) communication. This is especially true with relation to issues that are of concern, such as interference and hearing impairment. The development of a large number of potential remedies has been done in response to these problems. The purpose of this part is to present a concise explanation of the research that has been undertaken in the field of ultra-wideband (mmWave) communication in the past, as well as the approaches that have been implemented to address challenges that have been encountered pertaining to communication [6].

A. Directional MAC Protocols

In the realm of directional millimeter wave (mmWave) networks, communication has been the focus of a multitude of multi-access control (MAC) solutions. Each of these solutions has been suggested with the objective of enhancing communication. When utilized in networks that are already experiencing congestion, traditional contention-based protocols, such as CSMA/CA (Carrier Sense Multiple Access with Collision Avoidance), incur increasing levels of contention and collision rates. This is because these protocols are designed to avoid collisions. When this happens, the consumption of resources is not optimal, and the operational latency is prolonged. This is a consequence of the fact that this occurs. Researchers have developed directional MAC strategies that make use of the directional qualities of ultra-wideband (mmWave) communication in order to solve these difficulties [7]. These techniques were developed in order to address the concerns that have been raised. The Directional Multi-Channel MAC (DMAC) protocol was developed with the purpose of reducing congestion and increasing the speed at which data is transmitted with more efficiency. It is designed to distribute

channels and beam orientations to nodes in a manner that is consistent with the conditions that are currently present in the network. Adaptive Beamforming MAC, often known as AB-MAC, is a protocol that makes use of dynamic adjustments to beamforming parameters in order to respond to the current channel conditions [8]. This is done with the purpose of enhancing the performance and stability of the connection.

B. Communication Failure Mitigation Techniques

Deafness and interference are two examples of communication problems that have been proposed as potential solutions for directed millimeter wave (mmWave) networks. Others have been proposed as potential solutions. By directing antenna beams toward particular receivers, a technique known as beamforming can improve signal reception while simultaneously reducing the amount of signal attenuation that could occur. Through the utilization of channel estimate technologies, such as pilot-based estimation and feedback systems, nodes are able to correctly determine the conditions of the channel and alter the transmission parameters accordingly. In dynamic industrial environments that are characterized by quickly changing operational conditions, it is crucial to acknowledge that these strategies may display limited effectiveness [9]. Acknowledging this fact is essential.

Techniques that utilize machine learning have demonstrated their promise to address the issues that are associated with lowering the number of communication failures that occur in millimeter wave (mmWave) networks. Deep Learning-based Channel State Estimation (DL-CSE) is a technique that makes use of neural networks to aid the understanding of complex channel properties and the accurate evaluation of channel states. Protocols for Media Access Control (MAC) that are based on reinforcement learning make use of techniques for reinforcement learning in order to improve MAC configurations and maximize network performance in dynamic environments. Despite the fact that these methods have been shown to result in significant increases in connection reliability and data transmission speed, they usually need a substantial amount of training data and computational resources, which limits their practical use in IIoT devices that have limited resources [10].

C. Gap in Existing Literature

Even though there has been recent advancements in millimeter wave (mmWave) communication and the implementation of measures to minimize communication failures, it is still extremely important to recognize and address the distinct challenges that are associated with directional communication within industrial Internet of Things (IIoT) networks. In certain cases, traditional techniques place a higher priority on enhancing the effectiveness of communication in fixed or uniform settings, while ignoring the dynamic nature of industrial contexts, which contain a wide variety of operating circumstances and communication requirements [11]. Regarding the usage of machine learning techniques for the identification and

resolution of communication difficulties inside mmWave-based Industrial Internet of Things (IIoT) networks, there is a paucity of scholarly investigations [12]. This is a problem because there is a lack of research in this area.

An unique machine learning approach is presented in this research study. The purpose of this approach is to identify instances of communication disruptions in directed industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) frequency band. The goal is to fill in the gaps that currently exist in this area of study. The purpose of this research is to provide a methodology that makes use of machine learning algorithms and IIoT device status metrics in order to precisely identify communication challenges and rapidly respond in order to limit the consequences that these difficulties have on network performance. In addition, we provide ML-DMAC, a MAC protocol that includes machine learning approaches to maximize performance. This is accomplished by boosting the throughput of packets and decreasing the amount of time that signals are unavailable during device-to-device communication. We give evidence of the efficacy of our proposed scheme and protocol in reducing communication failures in directional mmWave-based IIoT networks by conducting stringent performance assessments. This demonstrates that our proposed scheme and protocol should be implemented.

III. PROPOSED COMMUNICATION FAILURE IDENTIFICATION SCHEME

Within the scope of this study, we provide a novel approach to machine learning that is designed to recognize instances of communication disruptions that occur within directed industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) frequency range. The current approach is one that has been developed with the express purpose of addressing the problem of hearing impairment. The methodology that has been proposed makes use of machine learning algorithms in order to investigate the status characteristics of Industrial Internet of Things (IIoT) devices and classify network failures as either interference or deafness. Our methodology makes it possible to take quick action to mitigate the negative impacts on network performance [13]. This is accomplished by effectively detecting the specific type of communication breakdown that has occurred. In this particular investigation, we are concentrating on a particular classification of industrial Internet of Things (IIoT) networks. These networks include a wide variety of Industrial Internet of Things (IIoT) devices. Millimeter wave transceivers and tuned antennas are included in the devices that have been listed above. All of the devices that are part of the Industrial Internet of Things (IIoT) have the capability to operate in either the transmit or receive mode, and they are also able to engage in peer-to-peer communication with the devices that are located nearby. There are a number of external factors that have the ability to affect the communication transmission between devices. These factors include interference, obstruction, and fluctuating channel conditions [14].

We extract relevant characteristics from the state parameters of Industrial Internet of Things (IIoT) devices in order to improve the effectiveness of machine learning in the classification of communication failures. This is done in order to improve the efficiency of machine learning techniques. Signal intensity, signal-to-interference-plus-noise ratio (SINR), beamforming thresholds, and channel parameters are all included in the list of defined attributes. Additionally, the categorization model takes into consideration ambient characteristics as input features [15]. These elements include the dynamic motion of the device, obstacles, and sources of disruption. A number of supervised machine learning techniques, such as support vector machines (SVM), random forests, and deep neural networks, are applied in this investigation for the purpose of classifying communication failures by means of the analysis of extracted features. Labeled datasets are used to train the classification algorithm. These datasets cover a wide variety of case studies, including scenarios in which communication breaks down, such as instances of deafness and interference [16]. When the model is in the training phase, it is able to acquire the ability to recognize patterns in the input attributes that are indicative of each particular type of communication failure. During the post-training phase, the classification model is installed on devices that are part of the Industrial Internet of Things (IIoT). This is done in order to encourage continuous network monitoring and the timely identification of any communication problems that may arise. The model will proceed to categorize the failure as either deafness or interference once it has been detected. This classification is accomplished by studying the patterns that are noticed in the input features. After determining the particular kind of malfunction that occurred, appropriate actions are conducted in order to restore the dependability and efficiency of the communication system [17].

Through the use of exhaustive simulations carried out in a variety of industrial settings, the purpose of our research is to evaluate the efficiency of the suggested method in identifying instances of communication breakdowns. This study assesses the usefulness and dependability of the system across multiple operational scenarios through the measurement of performance metrics, including classification accuracy, detection latency, and mitigation effectiveness [18]. The incorporation of the proposed method for identifying communication failures into the Markov Chain (MAC) protocols that are already in use has the potential to increase the protocols' resistance to communication failures. The system makes it possible for MAC protocols to alter their operations in reaction to mistakes, which optimizes resource allocation, scheduling, and beamforming parameters [19]. This is done in order to reduce the negative influence that the system has on the performance of the network. In order to successfully identify and classify instances of communication disruptions in directed industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) frequency band, the methodology that has been presented makes use of machine learning techniques. Through the utilization of timely intervention and mitigation measures, the methodology that has been developed enhances the

dependability and efficiency of communication in dynamic industrial settings.

IV. ML-DMAC: MACHINE LEARNING ENHANCED MAC PROTOCOL

The Machine Learning Enhanced Medium Access Control (MAC) protocol known as ML-DMAC has been devised specifically for easing directional device-to-device (D2D) communication in industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) band. Through the utilization of real-time feedback from the system, the fundamental objective of ML-DMAC is to be able to improve the suggested methodology for detecting communication difficulties. This will be accomplished through the automatic adaption of MAC settings. For the purpose of improving the dependability and efficiency of communication within dynamic industrial contexts, the ML-DMAC implementation makes use of machine learning approaches [20]. The optimization of data transfer rates and the reduction of connection latency are the means by which this objective is accomplished. Conventional media access control (MAC) approaches that are utilized in millimeter wave (mmWave) communication usually rely on pre-established parameter settings and periodic channel monitoring in order to manage the flow of data between nodes. On the other hand, the effectiveness of these protocols may be limited in dynamic industrial settings due to the rapidly changing conditions of the network and the requirements for communication. With the help of machine learning approaches, the ML-DMAC solution is able to address this particular challenge by dynamically modifying MAC settings while taking into consideration the current network conditions and performance data [21].

The ML-DMAC strategy employs supervised or reinforcement learning methods to elucidate the correlation between network state characteristics and the optimal configurations of multiple access control (MAC) parameters. The MAC protocol employs an analysis of network behavior across diverse operational circumstances during the training phase. This research facilitates the recognition of trends that enhance performance regarding data transfer rates, response times, and network reliability. The trained model is subsequently employed on devices inside the Industrial Internet of Things (IIoT) to dynamically adjust the parameters of the Media Access Control (MAC) system according to the prevailing network conditions [22]. The ML-DMAC technology can dynamically alter MAC parameters using data from the communication failure detection mechanism. The modifications encompass contention window size, transmission power, beamforming direction, and access priority. The ML-DMAC algorithm assesses the nature and magnitude of communication loss and subsequently modifies the MAC settings to mitigate its adverse consequences. In instances when deafness arises from misalignment or obstruction, the ML-DMAC technique can be employed to modify the beamforming parameters to steer the antenna beams toward the selected receiver. The change indicated earlier resulted in enhanced signal

reception and a decrease in the duration of hearing impairment [23]. The ML-DMAC system effectively integrates the method designed for identifying communication faults. This enables the quick collection of input concerning network performance and communication breakdowns. The ML-DMAC methodology facilitates the acquisition of information regarding the nature and severity of communication failures. This information facilitates the Media Access Control (MAC) protocol in effectively prioritizing access to less congested channels, modifying beamforming designs, and optimizing resource allocation. These initiatives aim to alleviate the detrimental impacts of breakdowns on the operation of electronic networks [24]. This paper evaluates the effectiveness of ML-DMAC through extensive simulations in various industrial settings, comparing its performance to traditional MAC protocols and modern machine learning approaches. An extensive assessment of the efficacy of ML-DMAC in improving communication reliability and performance in dynamic industrial settings is performed by analyzing performance metrics like throughput, latency, deafness duration, and energy efficiency [25].

By applying the learned deep neural network (DNN) model, the sender can precisely assess whether the network failure is owing to a compromised signal or a deficit in responsiveness. Presented below is an algorithm that highlights the sequential processes that are involved in the ML-DMAC that has been suggested. In the event that the DCTS timeout occurs, the sender will make an effort to gather further information from the trained DNN model concerning the underlying reason of the network issue. The

input parameters that were currently being utilized during the DRTS broadcast will be included in this request. The machine learning agent will initially use the deep neural network (DNN) model in the event that a DCTS timeout occurs. This is done in order to make a prediction regarding the underlying reason of the network challenge. Retransmission is a method that involves a systematic increase in the size of the backoff window through the employment of an exponential-based function. This is done in the event that the failure of the network is ascribed to signal damage. As an alternative to participating in retransmission, the system evaluates its transmission queue and establishes communication with the nodes that are adjacent to it. Here is a visual illustration of the method that was discussed earlier, which can be found in Figure 2.

According to the transmission queue, it is the responsibility of Node A to send data frames to destination nodes B, C, D, and C in a specific order. This responsibility is denoted by the transmission queue. There is a Data Relay Transmission System (DRTS) frame that is sent from node A to node B for the purpose of transmitting the data frame, as can be seen in Figure 2. It is possible that a connectivity problem between Node B and Node 3 is the cause of the fact that Node B is unable to receive the DRTS packet that was sent from Node A. The result of this was that node A suffered a DCTS timeout event, which is seen in Figure 2. In order to determine the underlying cause of the network failure, whether it is due to a compromised signal or an issue with the capabilities of node A to receive signals, node A sends a request to the trained deep neural network (DNN) model by utilizing its current state knowledge.

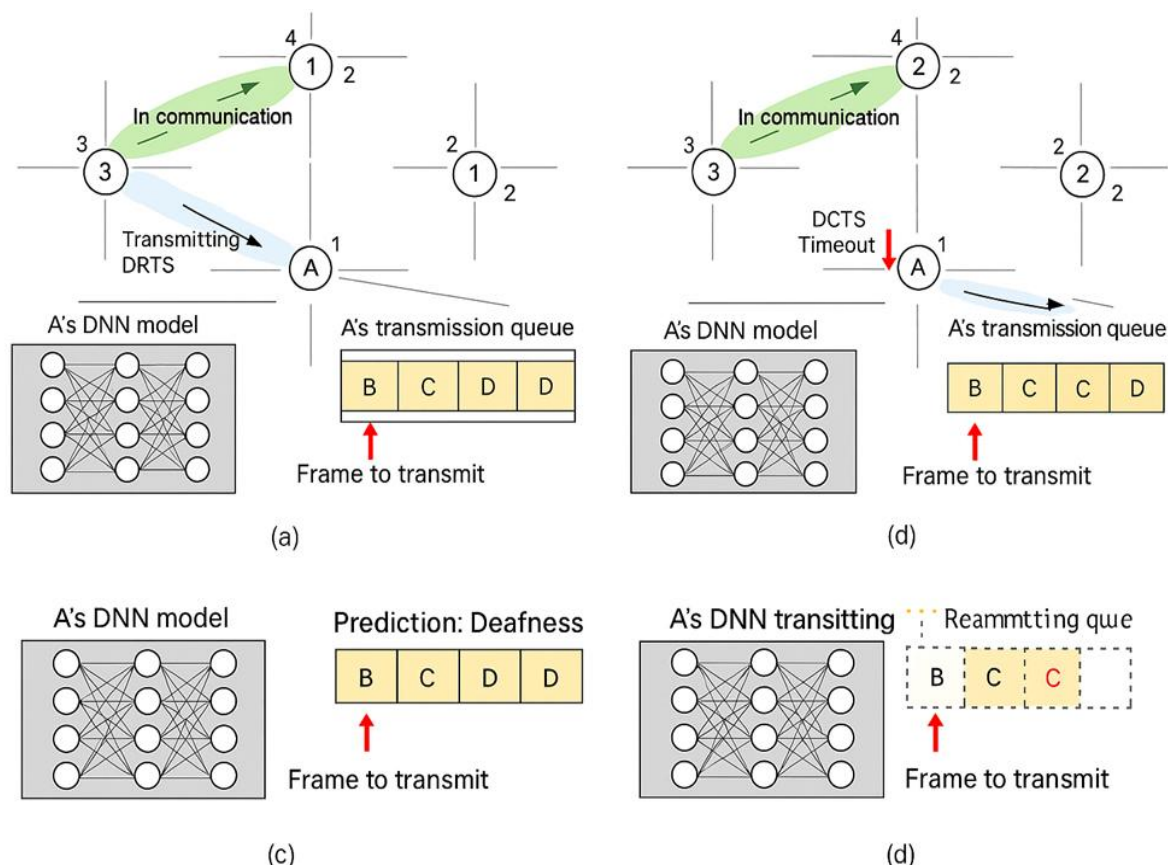


Fig. 2. An example of how the ML-DMAC process works. a) Node A sends DRTS to node B. b) The DCTS pause event is sent to node A. c) The taught DNN model can guess the state of deafness. d) Node A sends DRTS to node C.

This is done in order to determine the source of the failure. For the purpose of making predictions concerning deafness, the deep neural network (DNN) model makes use of the data that is presented in Figure 4(c). Comparatively speaking, the purpose of Node A is to identify the data frame within the transmission queue that is scheduled for a different antenna orientation than that of Node B. Given that node C is situated in a different direction from node B, as shown in Figure 2, Node A sends the Distributed Reservation Time Slot (DRTS) to node C in order to transfer the frame to node C. This is done in order to fulfill the goal explained in the previous sentence. There is an addition made to the transmission queue of node A, which contains the packet that was meant for node B.

The ML-DMAC algorithm offers a comprehensive solution for effectively managing communication failures in directed industrial Internet of Things (IoT) networks. It integrates without any trouble with the communication failure identification technique that has been proposed, making it a solution that is both comprehensive and effective. Real-time feedback is applied within the framework of the ML-DMAC approach in order to automatically alter MAC settings in a dynamic manner. This is accomplished through the utilization of the technique. As a result of the application of this technique, the negative impacts that communication failures have on the overall performance of the network are mitigated, which ultimately leads to an improvement in the throughput of communication and the dependability of communication [26]. The ML-DMAC protocol is a novel approach to the MAC protocol that makes use of machine learning techniques to enhance the efficiency of directional industrial Internet of Things networks that run in the millimeter wave (mmWave) frequency band. This protocol was specifically designed to improve the efficiency of these networks. Two of the most important objectives are to enhance the effectiveness of the system and to shorten the duration of hearing impairment events. The ML-DMAC system increases the dependability and efficiency of communication in dynamic industrial environments in a number of different ways. One of these methods is through the dynamic adjustment of MAC settings, which is guided by real-time data obtained from a mechanism designed to identify communication difficulties.

V. RESULTS AND ANALYSIS

The findings of the performance evaluation show that the communication failure detection technique presented in this study is able to successfully identify and categorize communication issues, which enables timely actions to limit the influence that these issues have on the performance of the network. The dynamic adjustment of MAC settings is accomplished by the utilization of real-time feedback from the communication failure diagnosis mechanism using the ML-DMAC MAC protocol. This feature leads to an increase in the pace at which data is sent, a decrease in the amount

of time that it takes for data to be transferred, and a reduction in the number of instances in which signal loss occurs. In addition, the incorporation of machine learning approaches into the MAC protocol provides ML-DMAC with the ability to adjust to a wide variety of network conditions and improve resource allocation, which ultimately results in improved energy efficiency and scalability. In conclusion, the solutions that have been described have the potential to considerably enhance the dependability and efficiency of communication in particular industrial Internet of Things (IoT) networks that operate within the millimeter wave (mmWave) frequency range.

In addition, a machine learning agent that has been trained in a grid topology is utilized in a random deployment scenario in order to evaluate the generalization capability of the suggested machine learning model. The mobility of IIoTDs in industrial systems is not taken into consideration in simulation scenarios because these devices are typically fixed in their places. Table 1 is a listing of the input parameters for the simulation.

TABLE I
SIMULATION PARAMETERS

Simulation parameter	Value
Transmit power	15 dBm
Receive sensitivity	-55 dBm
Number of antennas	6
Degree of each antenna	$\pi/3$ (rad)
Packet size	1400 b
Data rate of transmission channel	54 Mbps
CWmin	16
CWmax	1024
Number of nodes	9, 16, 25, 36, 49
Simulation duration	100 s

It was decided to construct a model in order to evaluate the potential effects of both grid deployments and random deployments. In the grid scenario, every single node communicates with neighboring nodes in four separate directions: up, down, left, and right. Every single node is able to communicate with the other nodes in the grid. Therefore, it is essential to impose a limitation of four data transfers per node in order to fulfil the requirements. As an illustration, the grid deployment that consists of sixteen nodes is depicted in Figure 3.

Within the context of the random deployment scenario, the nodes were dispersed in a random fashion throughout a territory that was 100 square meters in size. In order to evaluate the generalization performance of the proposed model, we use a machine learning agent that has been trained using a grid topology. This agent is deployed in a random deployment scenario. In order to account for the permanent placement of Devices IIoTDs in industrial systems, the notion of mobility is not incorporated into simulation scenarios.

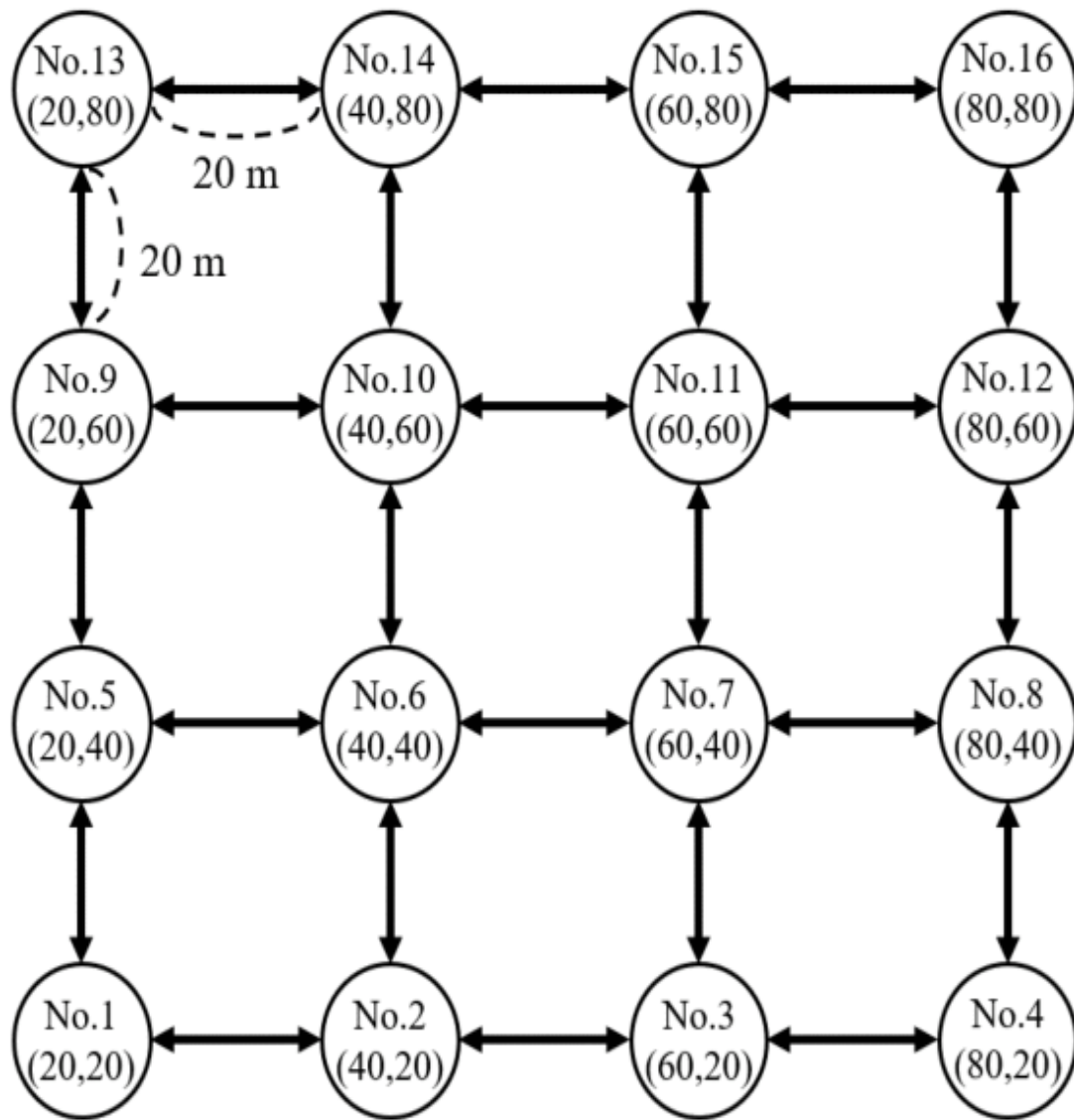


Fig. 3. The number of nodes is a factor in the grid deployment scenario

The experimental findings of the performance evaluation of the data flow rate are depicted in Figures 4 and 5, respectively. It was decided to conduct a comparative analysis in order to investigate the performance of three different MAC protocols in grid deployment as well as random deployment scenarios. As a result of the fact that the grid deployment scenario and the random deployment scenario each had 36 nodes, the total number of nodes in both situations was 36. The data flow that was observed displayed a spectrum of varied data rates that ranged from 1000 to 2000 kbps, with rates increasing by 200 kbps at each increment. When compared to the DMAC, the ML-DMAC regularly demonstrates higher throughput characteristics, with a margin that ranges from 13.4% to 31.4%. Furthermore, in terms of throughput, the ML-DMAC solution has greater performance in comparison to the CRCM, demonstrating a margin that ranges from 19.9% to 60.0% during the processing of data. A trained deep neural network (DNN) model that is able to determine whether a node is experiencing audio impairment can be utilized by ML-DMAC in order to solve the issue of deafness. This

model is able to determine whether or not a node is experiencing audio impairment. When compared to other protocols, the CRCM protocol has a lower throughput. This is because the CRTS/CCTS mechanism incurs a substantial amount of communication cost, which results in a lower throughput. Furthermore, when compared to AL-DMAC, which places an exclusive emphasis on reinforcement learning, ML-DMAC demonstrates a significant improvement in performance, with the range of 10% to 20% showing a noteworthy improvement. Despite the fact that AL-DMAC incorporates techniques to enhance data transmission based on channel circumstances, it does not have a system for detecting and mitigating deafness. On account of this, the presence of hearing impairment led to an increase in the number of retransmission attempts, which ultimately resulted in a drop in the overall data transfer rate. As a result of the data that is shown in Figure 5, it is possible to make the observation that the ML-DMAC technique displayed the least amount of hearing loss in comparison to the other two treatments.

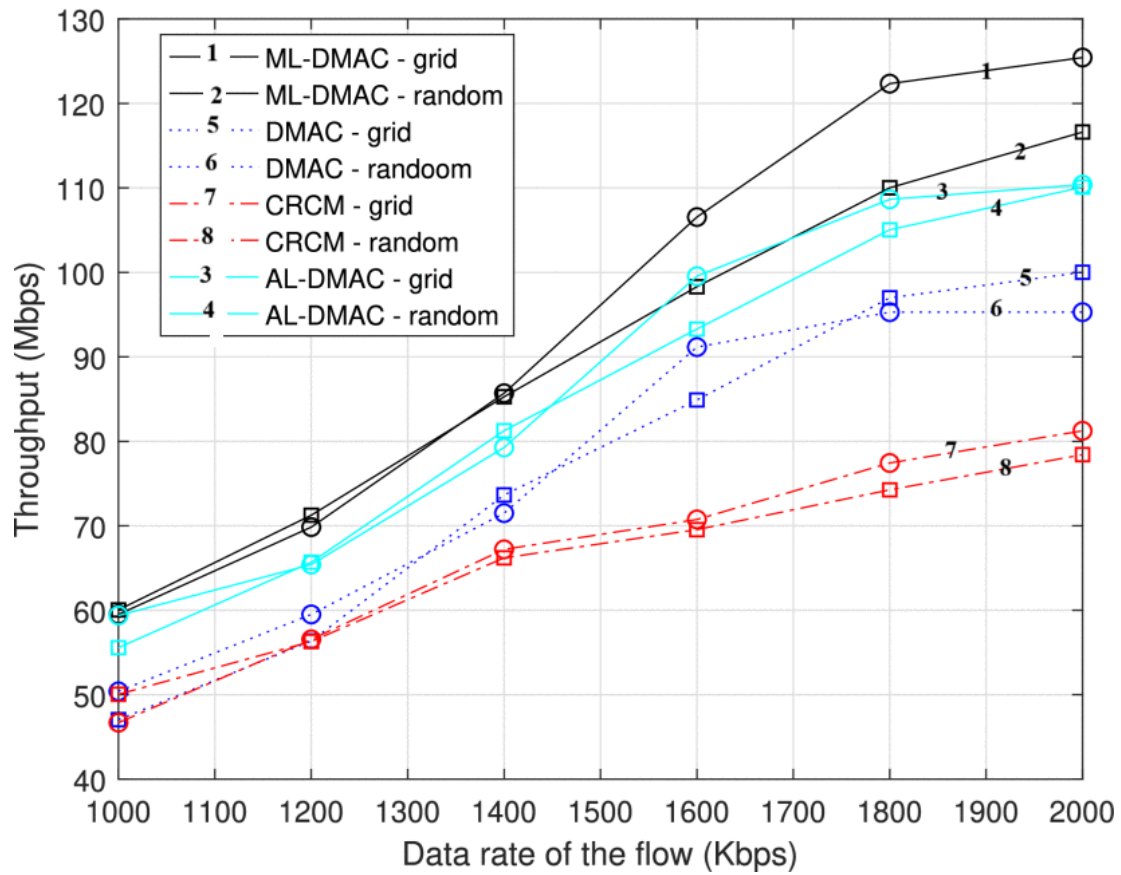


Fig. 4. The ratio of throughput to the data transfer rate

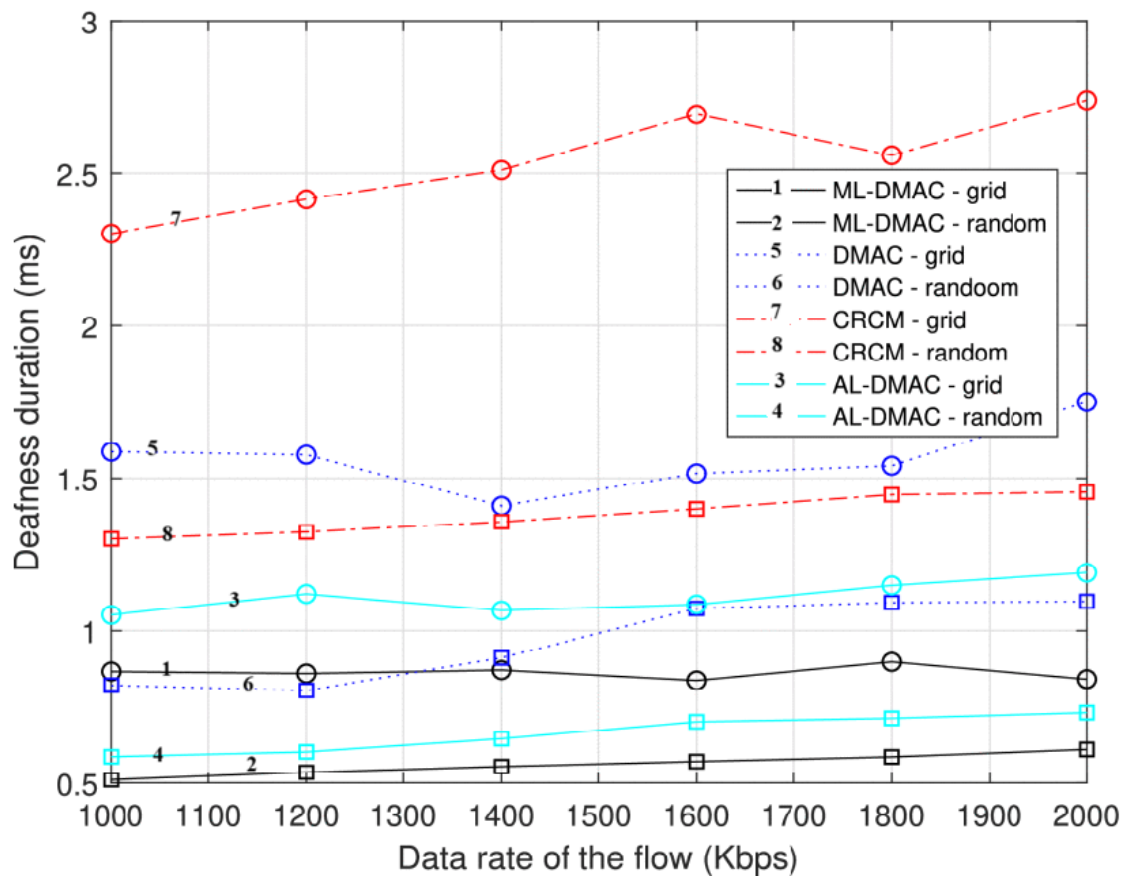


Fig. 5. The duration of deafness exceeds the data transfer rate

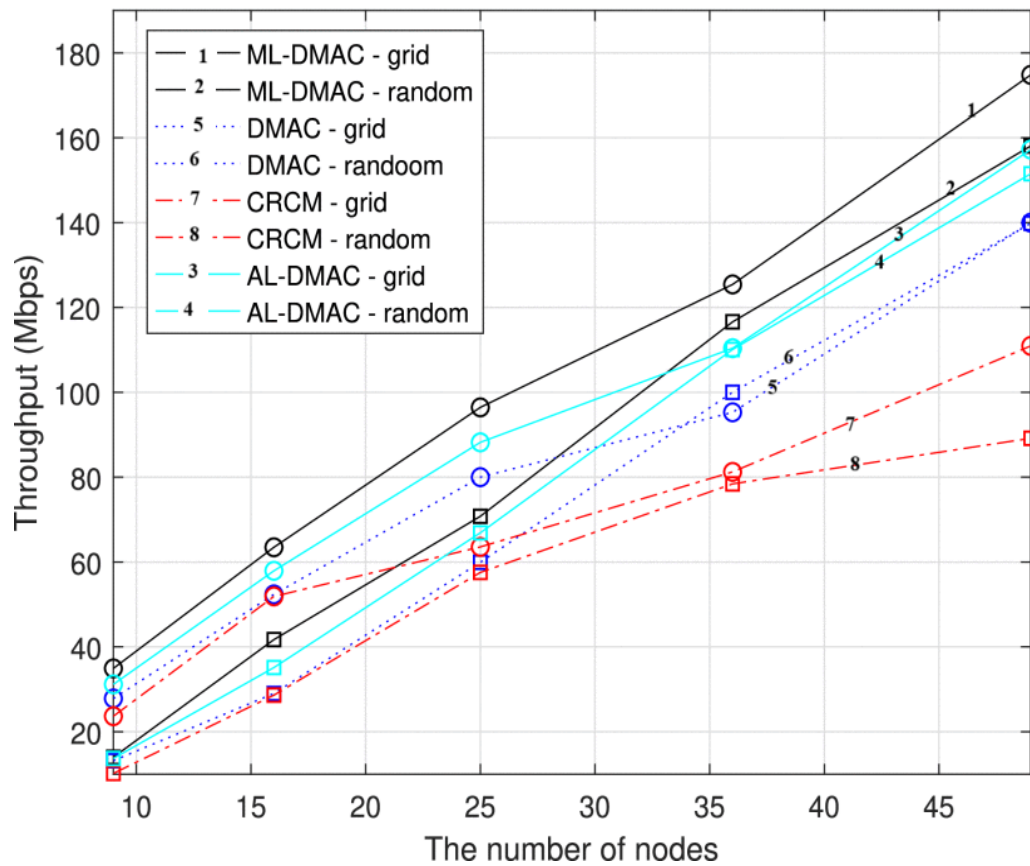


Fig. 6. Throughput as a function of node count

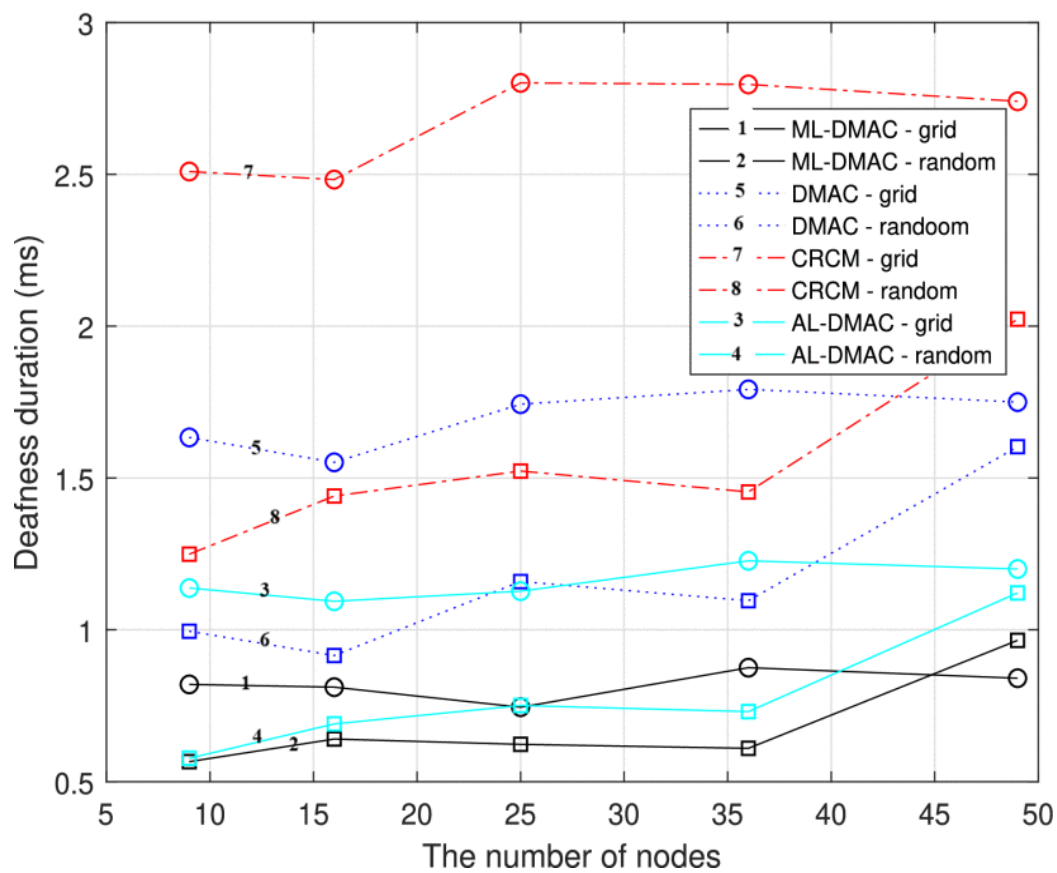


Fig. 7. Duration of deafness multiplied by the number of nodes

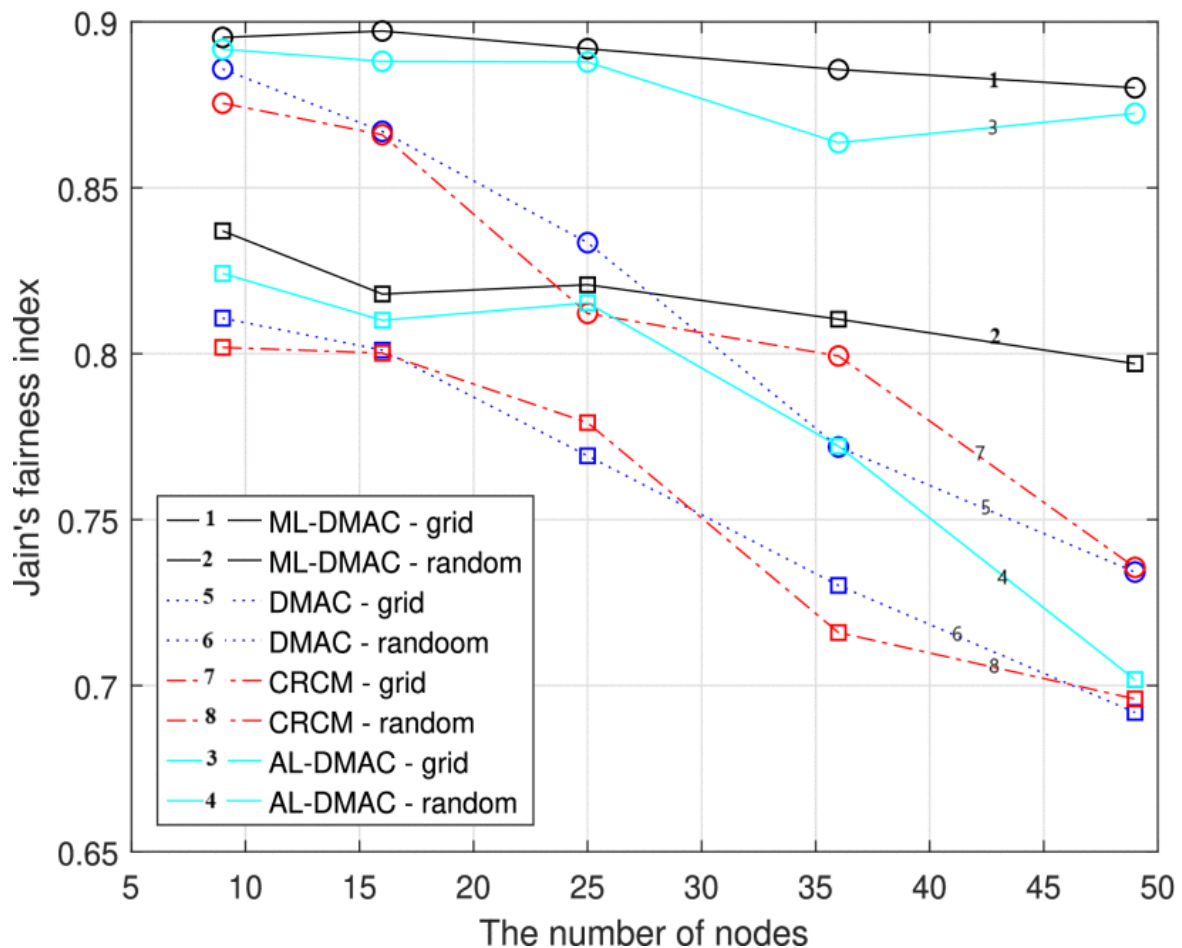


Fig. 8. The distribution of Jane's fairness index across the number of nodes in a grid deployment scenario

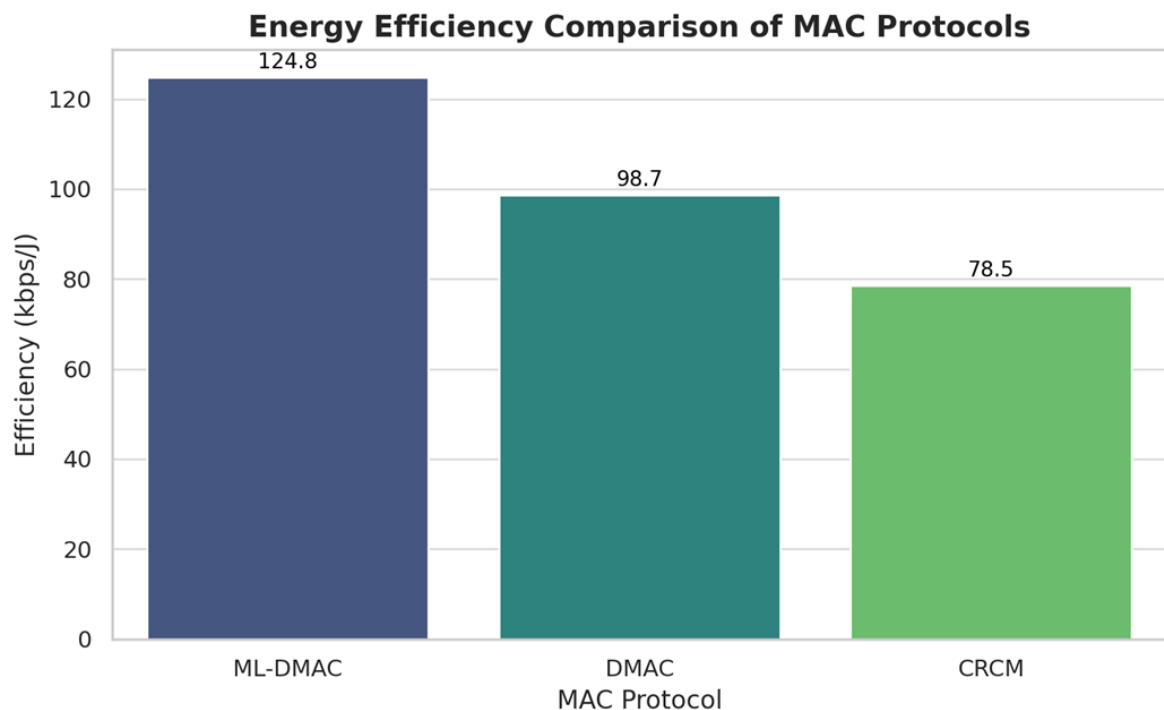


Fig.8. Energy Efficiency Comparison of MAC Protocols

By directing the intensity of the beam in a different direction upon detection, the ML-DMAC technology is able to efficiently reduce the amount of time that hearing loss lasts. It was found that the duration of auditory impairment

following CRCM surgery was considerably longer when compared to the duration of impairment following alternate treatment methods. The underlying element that contributes to this phenomenon is the longer duration of the CRTS /

CCTS / DDATA / DACK transactions, in contrast to the DRTS/DCTS/DDATA/DACK transactions at the same time.

A performance study was conducted by altering the distribution of nodes within the grid and utilizing random deployment scenarios. The data transfer rate was set at 2000 kilobits per second. The quantity of nodes ranged from 9 to 49. With the escalation in the number of nodes, there is a proportional rise in both network density and network traffic volume. Figures 6 and 7 illustrate the outcomes of the performance assessment about the quantity of nodes. Figure 6 demonstrates that ML-DMAC displays enhanced throughput performance relative to DMAC and CRCM. A performance study was conducted by altering the distribution of nodes within the grid and utilizing random deployment scenarios. The data transfer rate was set at 2000 kilobits per second. The quantity of nodes ranged from 9 to 49. With the escalation in the number of nodes, there is a proportional rise in both network density and network traffic volume. Figures 6 and 7 illustrate the outcomes of the performance assessment about the quantity of nodes.

Figure 6 illustrates that ML-DMAC exhibits superior throughput performance compared to DMAC and CRCM. The ML-DMAC algorithm consistently demonstrated superior throughput compared to DMAC, with an improvement ranging from 6.2% to 43.7%. ML-DMAC exhibited superior performance compared to CRCM, with a maximum margin ranging from 19.9% to 77.3%. The ML-DMAC model demonstrated superior performance compared to the AL-DMAC model, with a difference ranging from 5% to 11%. This phenomenon can be attributed to two sources. The ML-DMAC protocol can identify cases of hearing impairment, enabling nodes to address this challenge and modify the wireless transmission to an alternative antenna position. As the number of nodes increases, the proportion of nodes experiencing significant traffic congestion also rises, thereby worsening the problem of signal interference. Figure 7 illustrates the duration of hearing impairment among individuals with varying node counts. The ML-DMAC model demonstrated the briefest duration of auditory impairment, aligning with the findings presented in Figure 5. In contrast, CRCM consistently exhibited the longest duration of deafness across all conditions tested.

Figure 8 illustrates the fairness index of Jane's system across two deployment scenarios, one with 36 nodes and a data flow rate of 2000 kbps. The observed difference in data flows per node between the grid and random deployment scenarios suggests that Jane's fairness score is comparatively higher in the grid scenario. The fairness score of ML-DMAC surpasses that of DMAC and CRCM, indicating its superior efficacy. The difference in Jane's fairness index between ML-DMAC and other protocols increases in proportion to the number of nodes. The increase in nodes and traffic intensity correlates positively with the probability of a particular node seizing control of the channel during transmission. The ML-DMAC system can identify hearing impairments and proactively redirect data flow, rather than relying on the completion of the communication process. Consequently, each individual node is now more likely to significantly improve the probability of successful data transmission.

The figure compares the energy efficiency of three MAC protocols—ML-DMAC, DMAC, and CRCM—in terms of the number of kilobits transmitted per joule of energy consumed. As illustrated, ML-DMAC outperforms both DMAC and CRCM significantly, achieving an energy efficiency of **124.8 kbps/J**, compared to **98.7 kbps/J** for DMAC and **78.5 kbps/J** for CRCM. This improvement demonstrates ML-DMAC's capability to optimize communication parameters dynamically, minimizing redundant retransmissions and maximizing throughput. Consequently, ML-DMAC offers a more sustainable and power-efficient solution for Industrial IoT environments where energy consumption is a critical constraint.

TABLE I
ENERGY CONSUMPTION AND DELIVERY EFFICIENCY COMPARISON.

Protocol	Energy Consumed (J)	Packets Delivered	Efficiency (kbps/J)
ML-DMAC	120.4	8 600	124.8
DMAC	142.3	7 900	98.7
CRCM	158.7	7 100	78.5

Table I highlights how ML-DMAC not only improves raw throughput and reliability but also delivers significantly better energy efficiency. Although all three protocols were tested under the same traffic load and deployment (36 nodes, 2 000 kbps), ML-DMAC consumed roughly 25% less energy than CRCM and about 15% less than DMAC. Coupled with delivering the highest number of packets, this yields an energy efficiency of 124.8 kbps/J—over 26% higher than DMAC and nearly 59% higher than CRCM. These gains stem from ML-DMAC's dynamic, learning-driven adjustments that reduce retransmissions and idle listening, making it particularly well-suited for power-constrained IIoT devices.

VI. CONCLUSION

A unique machine learning approach is introduced in this research study with the idea of overcoming communication hurdles in directed industrial Internet of Things (IIoT) networks that operate within the millimeter wave (mmWave) frequency band. This research study was carried out specifically for the purpose of achieving this goal. In order to identify communication breakdowns, the suggested method makes use of techniques that are associated with machine learning. For the purpose of analyzing the status attributes of Industrial Internet of Things (IIoT) devices and categorizing network problems as either perceptual impairment or communication interruption, these algorithms are utilized. By utilizing this technique, which involves accurately recognizing the type of communication breakdown, it is feasible to promote early intervention in order to decrease the impact on network performance. This is achievable because of the fact that this strategy involves it. On top of that, ML-DMAC is a MAC protocol that has been developed with the intention of maximizing the efficiency of its operational capabilities. In order to achieve optimization, this protocol makes use of techniques that are associated

with machine learning. The current protocol was developed specifically for the purpose of operating in conjunction with a system that is able to recognize instances of communication failures. This was done with the objective of functioning simultaneously with the system. Because of this improvement, the process of automatically modifying MAC values in response to real-time feedback is simplified and made more straightforward. The implementation of ML-DMAC leads to improvements in the speed at which data is communicated, reductions in the amount of time it takes to receive information, and a reduction in the amount of communication downtime that occurs within the context of direct-to-device communication. All of these benefits are brought about by the improved speed of data transmission. The occurrence of this phenomenon offers a contribution to the improvement of the dependability and efficiency of communication capacities within the context of dynamic industrial settings. In the context of this research endeavor, the approach that is being proposed is meant to make use of machine learning strategies in conjunction with the ML-DMAC MAC protocol in order to identify issues that are associated with communication. This method provides effective solutions that have the potential to enhance the dependability and effectiveness of communication in directed industrial Internet of Things networks that function within the mmWave frequency band. It is suggested that future research should place a premium on the validation of the current methodologies in practical industrial settings, as well as the examination of advanced machine learning techniques, with the objective of enhancing the resilience and efficacy of communication. This is in order to achieve the goal of improving communication. In addition, these technological breakthroughs play a significant role in the development of communication infrastructures that are not only dependable but also effective in order to get ready for the forthcoming era of industrial Internet of Things (IoT) systems.

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