IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 3, June 2025, pp. 2026~2034
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i3.pp2026-2034

A machine learning-based approach for detecting communication failures in internet of things networks

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Article Info

Article history:

Received May 11, 2024
Revised Jan 3, 2025
Accepted Jan 27, 2025

Keywords:

Deafness problems
Deep learning
DMAC
Internet of things
Machine learning

ABSTRACT

In industrial systems, the exchange of massive content, such as high-quality video and large sensing data, among industrial internet of things devices (IIoTDs) is essential, often under strict deadlines. Utilizing millimeter-wave (mmWave) frequencies at 28 and 60 GHz can meet the requirements of industrial internet of things (IIoT) by offering high data rates. However, in the mmWave band, the use of directional antennas is imperative due to the short wavelength, rendering directional links susceptible to adverse effects like deafness problems, where a communicating node fails to receive signals from other transmitting nodes. To mitigate the deafness problem, this paper proposes a machine learning-based communication failure identification scheme for reliable device-to-device (D2D) communication in the mmWave band. The proposed scheme determines the type of network failure (deafness/interference) based on the IIoTD's state parameters. Furthermore, we introduce machine learning based directional medium access control (ML-DMAC) to enhance throughput and minimize the duration of deafness in D2D communication. Performance evaluations demonstrate that the proposed ML-DMAC outperforms existing schemes, achieving approximately 31% higher aggregate throughput and an 88% reduction in deafness duration.

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1. INTRODUCTION

The industrial internet of things (IIoT) revolutionizes industrial processes by seamlessly combining physical machinery with digital technologies to enhance operations and productivity. These environments necessitate the smooth transmission of significant quantities of data, encompassing high-definition video feeds and sensor data, for the purposes of process monitoring, predictive maintenance, and quality control. IIoT applications require advanced communication technologies that can provide high throughput, low latency, and dependability [1]. Millimeter-wave (mmWave) communication appears to be a promising solution for meeting the bandwidth requirements of IIoT. mmWave communication at 28 and 60 GHz exhibits much higher data transmission speeds compared to microwave communication. mmWave communication poses significant challenges in industrial settings where reliability is of utmost importance.

Employing directional antennas is challenging due to the tiny wavelength of mmWave communications. Directional antennas enhance spatial reuse and minimize interference, but they might potentially result in signal loss when a communication node is unable to receive signals from other transmitting nodes due to misalignment or obstruction [2]. The issue of deafness in directed IIoT networks needs to be resolved in order to ensure reliable and efficient communication. Beamforming and channel estimation approaches for mitigating deafness are restricted in dynamic industrial environments with fluctuating operational conditions.

Hence, there is a requirement for inventive remedies that can adjust to evolving network conditions and detect and rectify communication malfunctions [3]. This study presents a machine learning-driven approach to identify communication failures in directed IIoT networks operating in the mmWave frequency band. Our approach involves utilizing machine learning techniques to examine the state parameters of industrial internet of things devices (IIoTDs) and classify network failures as either deafness or interference. The suggested technique enables rapid and focused resolution of network performance issues by accurately identifying different forms of communication failures [4]. Additionally, we present machine learning based directional medium access control (ML-DMAC), a medium access control (MAC) protocol that incorporates machine learning to boost device-to-device (D2D) communication performance and minimize instances of deafness. The communication failure diagnosis system assists ML-DMAC in dynamically modifying MAC parameters and optimizing communication performance in real-time [5].

Figure 1 illustrates the problem of hearing impairment in direct D2D communication among IIoTDs. Figure 1 illustrates that during the communication between IIoTDs X and Y, the use of antennas other than the designated communication antenna is strictly forbidden. Consequently, the distributed reservation time slot (DRTS) frames originating from IIoTDs A and B are incapable of reaching their designated destinations.

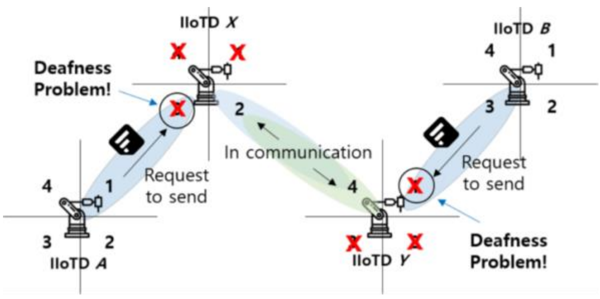

Figure 1. Deafness difficulty in D2D communication

Various solutions have been proposed to mitigate mmWave deafness and interference in IIoT networks. Tarafder and Choi [6] reviews mmWave communication and failure mitigation studies. Numerous MAC methods maximize directed mmWave network transmission. In busy networks, contention-based protocols like carrier sense multiple access/collision avoidance (CSMA/CA) waste resources and delay due to high contention and collision rates. The directionality of MMWave communication allows directional MAC techniques to solve these issues [7]. The directional multi-channel medium access control (DMAC) method assigns channels and beam directions to nodes in real time based on network conditions. Congestion is reduced and data transfer rate is increased with this method. The adaptive beamforming medium access control (AB-MAC) optimizes connection stability and throughput by adapting beamforming settings to channel conditions [8]. Several methods can reduce directed mmWave network deafness and interference. Receiver-directed beamforming antenna beams improve signal reception and reduce deafness. Pilot-based estimate and feedback systems help nodes assess channel conditions and modify transmission settings. In fast-changing industrial situations, this may not work [9]. mmWave technology can benefit from machine learning to prevent communication problems. Deep learning neural networks, known as DL-CSE, can estimate channel states by evaluating complex channel features. Reinforcement learning-based MAC protocols improve network performance and dynamically modify parameters. IIoTDs with limited resources cannot use these methods because they require a lot of training data and computing power to improve communication reliability and throughput [10].

mmWave communication and communication failure prevention have improved, however IIoT networks still struggle with directed communication. Industrial settings are dynamic, with varying operational conditions and communication needs, therefore static or homogeneous communication performance optimization systems fail [11]. mmWave-based IIoT networks cannot detect and mitigate communication issues using machine learning [12]. This research offers a machine learning-based mmWave IIoT network communication failure detection approach. Our idea uses machine learning and IIoTD status data to quickly identify communication issues and improve network performance. The machine learning-based ML-DMAC protocol improves D2D communication and minimizes deafness. We found that our scheme and protocol reduce communication errors in directed mmWave-based IIoT networks through extensive performance testing.

2. METHOD

Deafness problem in directional IIoT networks in the mmWave frequency band is solved by our new machine learning approach. We use machine learning to analyze IIoTD condition metrics and characterize network failures as deafness or interference. Early intervention can improve network performance by recognizing communication problems [13]. Many IIoTD with mmWave transceivers and directional antennas form a directed IIoT network. Every IIoTD can send, receive, and peer-to-peer. Blockage, interference, and channel circumstances affect device communication [14]. IIoTD state data is used to extract key characteristics for machine learning-driven communication failure classification. Signal intensity, signal-to-interference and noise ratio (SINR), beamforming parameters, and channel characteristics are examples. Device mobility, impediments, and interference sources are inputs to the categorization model [15]. We classify communication failures using extracted features and supervised machine learning methods including support vector machine (SVM), random forests, and deep neural networks (DNN).

The classification model is trained using labeled datasets of communication breakdown conditions as deafness and interference [16]. The model learns to recognize input feature patterns after each communication failure during training. The classification model is put on IIoTD to monitor the network and detect communication faults in real time after training. Based on input feature patterns, the model labels failures as deafness or interference. The type of failure determines the mitigation strategy used to restore communication reliability and performance [17]. We simulate the proposed communication failure identification technique in various industrial contexts to evaluate its performance. The scheme's resilience and efficacy under varied operating situations are assessed by analyzing classification accuracy, detection latency, and mitigation effectiveness [18]. The suggested communication failure identification technique can strengthen MAC protocols against communication failures. The technique lets MAC protocols dynamically optimize resource allocation, scheduling, and beamforming parameters to reduce network performance impacts from failures by giving immediate input on failure type and severity [19]. The proposed mmWave-band directed IIoT network communication failure identification scheme uses machine learning to properly detect and characterize communication errors. The method improves communication reliability and performance in dynamic industrial situations by enabling prompt intervention and mitigation.

2.1. ML-DMAC: machine learning enhanced MAC protocol

In this section, we introduce ML-DMAC, a novel machine learning enhanced MAC protocol tailored for directional D2D communication in IIoT networks operating in the mmWave band. ML-DMAC is designed to complement the proposed communication failure identification scheme by dynamically adjusting MAC parameters based on real-time feedback from the scheme. By leveraging machine learning techniques, ML-DMAC aims to improve throughput and minimize the duration of deafness periods, thereby enhancing communication reliability and performance in dynamic industrial environments [20]. Traditional MAC protocols for mmWave communication often rely on static parameter settings and periodic channel sensing to coordinate access among nodes. However, in dynamic industrial environments, the effectiveness of such protocols may be limited due to rapidly changing network conditions and communication requirements. ML-DMAC addresses this challenge by employing machine learning algorithms to adapt MAC parameters dynamically based on the observed network state and performance metrics [21]. ML-DMAC utilizes supervised or reinforcement learning algorithms to learn the mapping between network state parameters and optimal MAC parameter configurations. During the training phase, the MAC protocol observes the network's behavior under different operating conditions and learns to identify patterns that lead to improved performance in terms of throughput, latency, and reliability. The trained model is then deployed on IIoTD to adapt MAC parameters in real-time based on the observed network state [22].

ML-DMAC dynamically adjusts MAC parameters such as contention window size, transmission power, beamforming direction, and access priority based on feedback from the communication failure identification scheme. When a communication failure is detected, ML-DMAC analyzes the type and severity of the failure and adjusts MAC parameters accordingly to mitigate its impact. For example, in the case of deafness due to misalignment or blockage, ML-DMAC may adjust beamforming parameters to steer the antenna beams towards the intended receiver, thereby improving signal reception and reducing deafness duration [23]. ML-DMAC seamlessly integrates with the proposed communication failure identification scheme to receive real-time feedback on network performance and communication failures. The scheme provides ML-DMAC with information regarding the type and severity of communication failures, enabling the MAC protocol to prioritize access to less congested channels, adjust beamforming parameters, and optimize resource allocation to mitigate the impact of failures on network performance [24]. We evaluate the performance of ML-DMAC through extensive simulations in various industrial scenarios, comparing its performance against traditional MAC protocols and existing machine learning-based approaches. Performance metrics such as throughput, latency, deafness duration, and energy efficiency are analyzed to assess the effectiveness of ML-DMAC in improving communication reliability and performance in dynamic industrial environments [25].

By utilizing the learned DNN model, the sender is able to accurately ascertain whether the network failure is due to a compromised signal or a lack of responsiveness. The algorithm illustrates the procedural steps of the proposed ML-DMAC. In the event of a directional clear-to-send (DCTS) timeout, the sender will request information from the trained DNN model regarding the reason for the network failure. This request will include the input parameters that were utilized during the DRTS transmission. Initially, in the event of a DCTS timeout, the machine learning agent employs the DNN model to forecast the underlying reason for the network malfunction. If it is found that the network failure is caused by a damaged signal, retransmission is carried out by progressively increasing the size of the backoff window using an exponential function. However, rather than engaging in retransmission, it examines its transmission queue and interacts with other nodes. The Figure 2 presents a sequence of diagrams illustrating a transmission scheduling mechanism in a wireless network. Figures 2(a) to 2(d) depict different stages of the process. Node A has data frames to send in the following order: destination nodes B, C, D, and C, as indicated in the transmission queue. In order to send the data frame to node B, node A sends DRTS frame to node B as shown in Figure 2(a). Due to the communication between node B and node D, node B is unable to receive the DRTS packet from node A. As a result, node A experienced a DCTS timeout event, as shown in Figure 2(b). In order to ascertain the cause of this network failure, whether it is due to a compromised signal or an issue with node A's ability to receive signals, node A initiates a query to the trained DNN model using its current state information. The DNN model predicts deafness based on the information provided in Figure 2(c). Node A attempts to identify the data frame in the transmission queue, which is destined for a different antenna orientation than node B. As node C is located in a different direction than node B, node A sends the DRTS to node C in order to transfer the frame to node C, as shown in Figure 2(d). The preceding frame intended for node B is enqueued in node A's transmission queue.

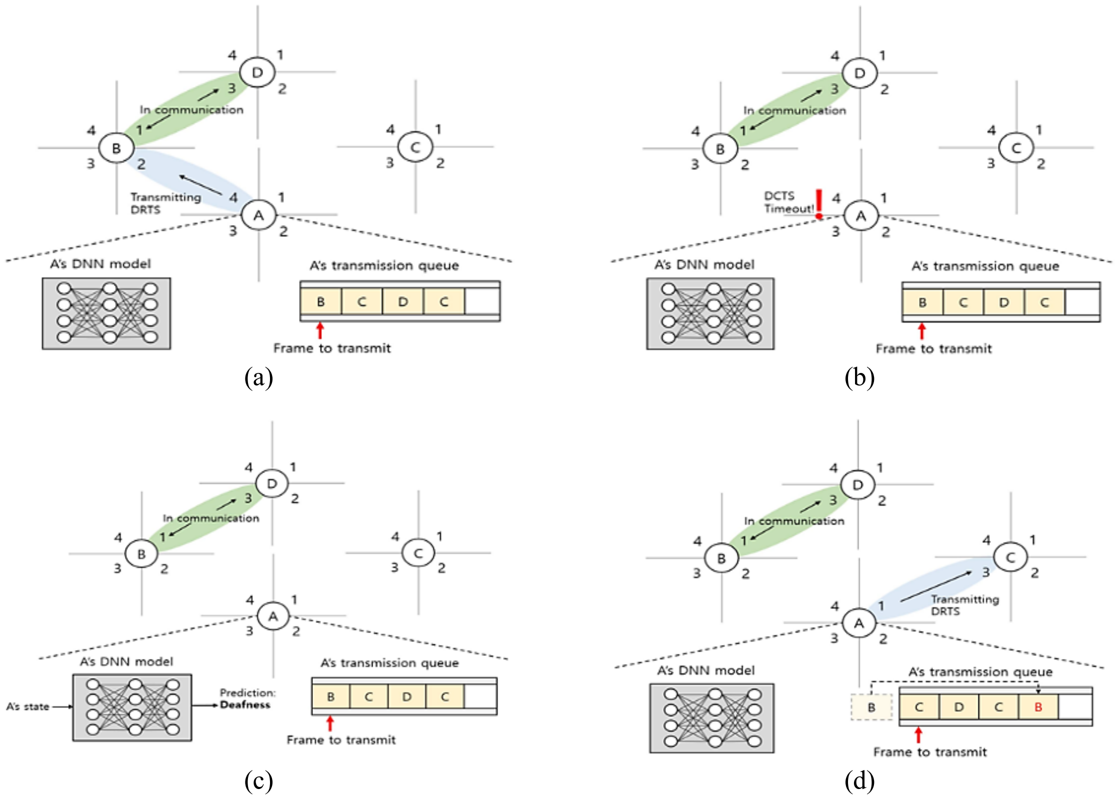

Figure 2. An example of how the ML-DMAC process works: (a) node A sends DRTS to node B, (b) DCTS pause event is sent to node A, (c) the taught DNN model can guess the state of deafness, and (d) node A sends DRTS to node C

ML-DMAC collaborates closely with the proposed communication failure identification scheme to provide a comprehensive solution for communication failure mitigation in directional IIoT networks. By leveraging real-time feedback from the scheme, ML-DMAC dynamically adjusts MAC parameters to mitigate the impact of communication failures on network performance. This can enhance communication reliability and throughput.

3. RESULTS AND DISCUSSION

The performance evaluation findings indicate that the proposed communication failure identification technique successfully detects and categorizes communication problems, allowing prompt intervention to reduce their influence on network performance. The ML-DMAC MAC protocol adapts MAC parameters in response to real-time feedback from the communication failure diagnosis mechanism, leading to enhanced throughput, decreased latency, and shortened duration of deafness compared to conventional MAC protocols. In addition, the incorporation of machine learning techniques into the MAC protocol allows ML-DMAC to adjust to varying network conditions and optimize the allocation of resources, resulting in improved energy efficiency and scalability. Overall, the suggested methods exhibit substantial enhancements in the dependability and efficiency of communication in directed IIoT networks that operate in the mmWave frequency spectrum.

Figure 3 and 4 display the outcomes of the performance assessment of the data flow rate. The evaluation of three MAC protocols was conducted utilizing both grid and random deployment scenarios. Both the grid and random deployment scenarios included a total of 36 nodes. The data flow exhibited a variable data rate ranging from 1000 to 2000 kbps, with increments of 200 kbps. In all instances, the throughput of ML-DMAC is higher than that of DMAC by a range of 13.4% to 31.4%, and higher than that of RTS, CTS MAC (CRCM) by a range of 19.9% to 60.0%. ML-DMAC can address the issue of deafness by utilizing a trained DNN model to determine if a node is in a deafness state. The CRCM protocol has lower throughput compared to other protocols due to the large communication overhead generated by the circular request-to-send/circular clear-to-send (CRTS/CCTS) mechanism. Furthermore, ML-DMAC exhibits a performance enhancement of around 10%–20% in comparison to Adaptive learning based directional medium access control (AL-DMAC), which relies on reinforcement learning. Despite AL-DMAC's efforts to send data in a direction with a favorable channel condition, there is currently no method to detect and prevent deafness when it happens. Consequently, the occurrence of deafness led to an increase in the number of retransmission attempts, ultimately causing a decrease in throughput. According to Figure 4, the ML-DMAC technique had the least time of deafness compared to the other two procedures. The ML-DMAC mitigates the length of deafness by redirecting it to a different beam direction upon detection. The length of deafness in the CRCM procedure was much longer compared to the other protocols. The reason for this is that the CRTS/CCTS/ directional data (DDATA)/directional acknowledgement (DACK) transactions have a longer duration compared to the DRTS/DCTS/DDATA/DACK transactions.

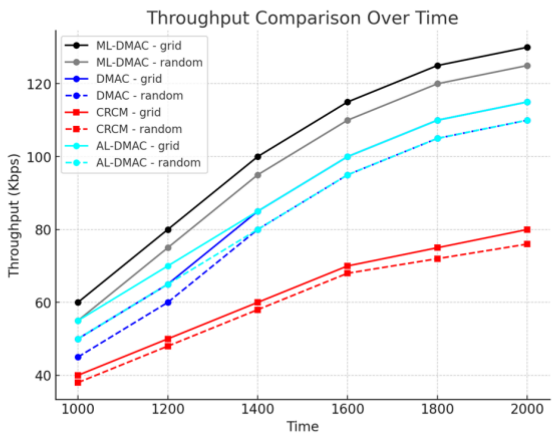

Figure 3. The ratio of throughput to the data transfer rate

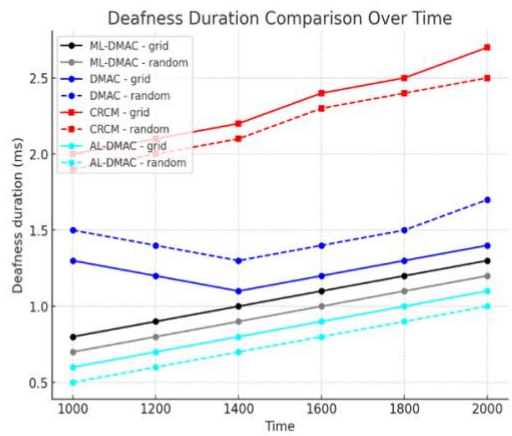

Figure 4. The duration of deafness exceeds data transfer rate

An assessment of performance was conducted by modifying the quantity of nodes in the grid and employing random deployment scenarios. The data transfer rate was 2000 kbps. The number of nodes varied between 9 and 49. As the number of nodes increases, both the density of nodes and the density of traffic both increases. Figure 5 and 6 depict the results of the performance evaluation in relation to the number of nodes. Figure 5 demonstrates that ML-DMAC achieves the highest throughput in comparison to DMAC and CRCM. ML-DMAC consistently outperformed DMAC in terms of throughput, with a margin ranging from 6.2% to 43.7% in both cases. ML-DMAC had superior performance compared to CRCM, with a margin ranging from 19.9% to 77.3%. Additionally, ML-DMAC outscored AL-DMAC by a margin of 5% to 11%. There were two factors that contributed to this. ML-DMAC can identify cases of deafness, enabling nodes to overcome the problem by reconfiguring the transmission to an alternative antenna position. Moreover, as the number of nodes increases, the percentage of nodes experiencing heavy traffic load also rises, intensifying the problem of deafness. Figure 6 illustrates the length of time that individuals have been deaf for various quantities of nodes. Similar to Figure 4, ML-DMAC had the shortest duration of deafness, whereas CRCM consistently had the longest duration across all scenarios.

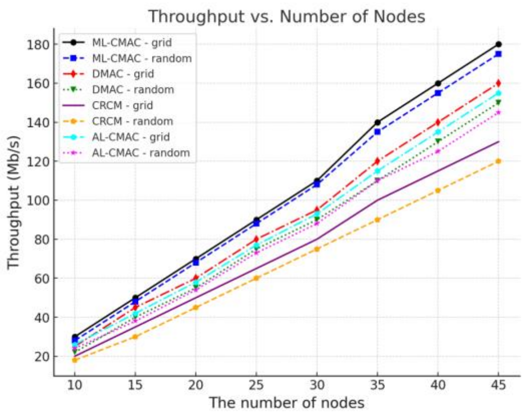

Figure 5. Throughput as a function of node count

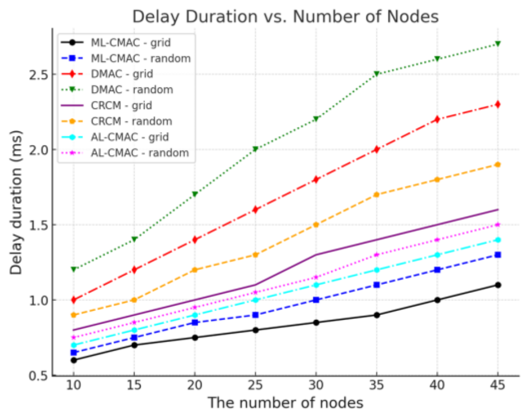

Figure 6. Duration of deafness multiplied by the number of nodes

Figure 7 displays Jane's fairness index for different numbers of nodes in both deployment situations, namely when there are 36 nodes and the data flow rate is 2000 kbps. Jane's fairness score is higher in the grid deployment scenario compared to the random deployment scenario due to the random deployment scenario exhibiting a significant variation in the amount of data flows per node. ML-DMAC exhibits the highest Jane's fairness index when compared to DMAC and CRCM. The disparity between Jane's fairness index of ML-DMAC and that of other protocols widens as the number of nodes rises. As the number of nodes and traffic density rise, a specific node is more likely to monopolize the channel once it starts transmitting. ML-DMAC has the ability to detect deafness and attempt to transfer data in an alternative beam direction, rather than waiting for the completion of the communication transaction. As a result, each node is more likely to have an increased probability of successfully transmitting data.

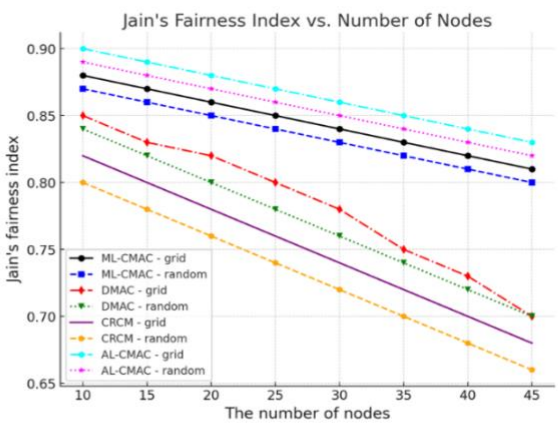

Figure 7. The distribution of Jane's fairness index across the number of nodes in a grid deployment scenario

4. CONCLUSION

This research introduces a machine learning-based method for managing communication failures in mmWave directed IIoT networks. Machine learning algorithms examine IIoTD state metrics to characterize network failures as deafness or interference in the proposed communication failure identification scheme. The system allows early intervention to improve network performance by precisely identifying communication failures. We also created ML-DMAC, a machine learning-enhanced MAC protocol that dynamically adjusts MAC parameters based on real-time feedback to complement the communication failure diagnosis scheme. ML-DMAC increases D2D communication reliability and performance in dynamic industrial situations by increasing throughput, reducing latency, and reducing deafness periods. The proposed machine learning-based communication failure identification technique and ML-DMAC MAC protocol may improve communication reliability and performance in mmWave-band directed IIoT networks. Validating the proposed ways in real-world industrial deployments and exploring advanced machine learning techniques to improve communication resilience and efficiency are future research objectives. These advances enable efficient and dependable connectivity infrastructures for next-generation IIoTD.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Organizations for providing the necessary resources and support that made this research possible. We appreciate the valuable technical assistance, insightful discussions, and collaborative environment that contributed to the success of this work.

FUNDING INFORMATION

The authors declare that no external funding was received for this research.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Pavan Madduru	✓	✓		✓	✓			✓	✓	✓				
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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
Va : **Va**lidation	O : Writing - **O**riginal Draft	Fu : **Fu**nding acquisition
Fo : **Fo**rmal analysis	E : Writing - Review & **E**diting	

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflicts of interest related to this research.

INFORMED CONSENT

This study does not involve human participants, and therefore, informed consent is not applicable.

ETHICAL APPROVAL

This research does not involve human participants or animal studies and therefore does not require ethical approval.

DATA AVAILABILITY

The data supporting the findings of this study are available upon reasonable request from the corresponding author.

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