Machine Learning-based Communication Failure Identification Scheme for Directional Industrial IoT Networks

Woongsoo Na[1], Namkyu Kim[2], Nhu-Ngoc Dao[3], and Sungrae Cho[4]

Abstract—**In industrial systems, massive content, such as high-quality video and a large amount of sensing data, should be exchanged between industrial Internet of Things (IIoT) devices under strict deadlines. The use of millimeter-wave (mmWave) frequencies of 28 and 60 GHz can satisfy the requirements of IIoT by providing a high data rate. In the mmWave band, it is necessary to use a directional antenna owing to its short wavelength. Consequently, directional links are vulnerable to adverse effects such as deafness problems, where a communicating node cannot receive signals from other transmitting nodes. To alleviate the deafness problem, in this paper, we propose 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) according to the IIoT device's state parameters. Based on the identification scheme, we additionally propose ML-DMAC to improve the throughput and minimize the deafness duration of D2D communication The performance evaluation shows that the proposed ML-DMAC outperforms existing schemes in aggregate throughput and deafness duration by approximately 31% and 88%, respectively.**

Index Terms—**Deep learning, directional MAC, deafness problems, and IoT networks.**

I. Introduction

RECENTLY Industrial Internet of Things (IIoT) technology has drawn attention for various applications, including factory automation, facility monitoring, inspection, and data acquisition [1]. Future IIoT applications are expected to require extremely high data rates (e.g., high-definition video streams) and high reliability (e.g., the command of human operator) and low latency (e.g., delay-sensitive data) between IIoT devices to maintain the entire industrial system [2].

To satisfy the above requirements, millimeter-wave (mmWave) can provide very high throughput (D2D) links, and maximize spatial reuse by using directional antennas [3]. For instance, 5th generation (5G) mobile new radio (NR) is an innovative technology that satisfies the above requirements of IIoT in the mmWave band [4]. Several companies such as Samsung and Ericsson try to realize the fourth industrial revolution, Industry 4.0, which aims to significantly improve the efficiency and flexibility of production processes through 5G NR.

However, the currently released 5G IIoT technology provides services within the cellular boundary, making it impossible to implement advantage of mmWave frequency in suburban and underdeveloped areas, where 5G infrastructure is not deployed. Furthermore, owing to the expensive 5G licensed band pricing policy, business operators have limitations in bringing about 5G Technology in the Industrial Domain. As an alternative, IEEE 802.11 ad [5] and ay [6] standard technologies provide short-range D2D links by utilizing the unlicensed band (60 GHz) with directional antennas[1]. However, mmWave D2D links are vulnerable to adverse effect such as dynamic blockage by obstacles and deafness problems owing to their very short wavelengths. In particular, a deafness problem occurs when a communicating node cannot receive signals from other transmitting nodes and prevents the activation of D2D links [7], [8].

In this study, we focused on the deafness problem that occurs when communicating in the mmWave band and proposed a machine learning-based communication failure identification scheme. The principal method was to identify the cause of failure when a network failure occurs [9]. Therefore, in the proposed scheme, each node learns from network failures such as interference and deafness, that occur during D2D communication, determines the cause of network failure and handle the situation appropriately. The contributions of this study are as follows:

- Existing work to resolve deafness is based on additional overhead (e.g., additional control frame, tone, and dual-channel). However, the proposed scheme can solve the deafness through learning by nodes without significant overhead. Furthermore, the proposed scheme is the first attempt to use machine learning to solve deafness to the best of our knowledge.
- We present neural network model to identify deafness and discuss performance analysis of neural network-based techniques and the possibility of using each technique according to network conditions.

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[1]The use of directional antennas is essential to compensate for high path-loss in the mmWave band.

The remainder of this paper is organized as follows. In Section II, we present a literature review on the directional MAC protocol and the deep learning approach for IIoT networks. Section III describes the system model for the proposed ML-DMAC. We describe our learning model and algorithm in Section IV. Simulation experiments are used to evaluate the performance of the proposed algorithm in Section V. Finally, Section VI concludes this paper.

II. Related Work

A. Directional MAC protocol

Directional antennas have many benefits compared with omni directional antennas. They can increase spatial reuse and network capacity. There are two main challenges in using directional antennas for transmission: a hidden-node problem and a deafness problem. The hidden-node problem occurs when the potential sender, which can collide with ongoing communication, does not receive a directional request to send (DRTS) or directional clear-to-send (DCTS) from currently communicating nodes. A deafness problem can occur when the sender transmits the DRTS to the receiver, and the receiver communicates with another directional antenna and blocks other antennas. These two problems significantly decrease network capacity. Several studies have been conducted on directional MAC protocols to solve these problems.

The initial MAC protocol research in [10], [11] focused on determining the beam direction by using an omni directional request to send/ omni-directional clear to send (ORTS/OCTS) packets. Each node sends a data packet after an ORTS/CTS transaction, using omni-directional communication. Even though these approaches use directional antennas, they do not exploit the advantage of directional antennas because communication is allowed between nodes at an omni transmission distance. Moreover, these studies have not addressed the problem of deafness. Directional MAC protocols using circular request to send/ circular clear-to-send (CRTS/CCTS) packets were proposed in [12]. The CRTS and CCTS were sequentially transmitted in all directions. Thus, a huge overhead is caused by the control frames, resulting in poor throughput. The schemes in [13], [14] use multi directional concurrent RTS/CTS transmission, which requires adaptive antenna arrays that enable power control. Because these approaches require sophisticated hardware, adapting them to the existing IIoTDs is difficult. A directional MAC protocol for basic stations (DMBS) in [15] tries to obtain the full advantage of spatial reusability in 802.11ad communication. DMBS determines the transmission direction using the CRTS/CCTS packets. Even though DMBS attempts to reduce the number of CRTS/CCTS transmissions, overhead still exists, limiting network capacity.

The existing schemes in [9], [16], [17] use an extra control channel. A dual-sensing directional MAC protocol was proposed in [16]. When the sender transmits a directional data (DDATA), the sender and receiver transmit busy-tone signals simultaneously. Other nodes that receive these signals postpone their transmissions. Two types of busy-tone signals were used, referred to as BT_1 and BT_2. However, DSDMAC cannot resolve the deafness problem. The deafness-aware MAC (DAMAC) was proposed in [9]. DAMAC sends the DRTS and DCTS to the data and control channels together. Therefore, even though the beam sector of the data channel is blocked, the node can distinguish between collision and deafness by the control channel. Because DAMAC uses two channels simultaneously, an extra delay does not exist to check that the transmission is available. A tone dual-channel MAC protocol with directional antennas was proposed by [17]. This scheme transmits ORTS and DCTS over the control channel and transmits directional data (DDATA) and directional acknowledgement (DACK) over the data channel. Negative clear-to-send (NCTS) and negative data (NDATA) are used to prevent collisions. However, additional transceivers are required for communication with extra control channels as proposed in [9], [16], [17], which makes it impossible to adapt to the hardware of the existing IIoTD.

B. Deep Learning Approach for IIoT networks

Deep reinforcement learning methods based on deep Q-learning networks (DQN) [18] and deep deterministic policy gradient (DDPG) [19] have been actively researched in IIoT systems. The DQN tries to model the Q-function, which represents the discounted cumulative reward of the state and action. On the other hand, DDPG attempt to model the policy itself, which generates action from the current state. Based on the states that represent the channel state information (CSI) and traffic requirements of IIoTDs, deep reinforcement learning-based approaches have been proposed [20], [21]. Multi-agent deep reinforcement learning algorithm based on multi-agent DDPG (MADDPG) was proposed to determine the channel assignment and task offloading strategy for mobile edge computing in IIoT networks [20]. IIoTDs are considered agents and cooperate with each other, resulting in a reduced computation delay. Dai *et al.* proposed a deep reinforcement learning scheme using an actor-critic network, which is a core part of DDPG [21]. The proposed scheme determines the optimal stochastic computational offloading policy. A smart manufacturing scheduling system was proposed in [22]. DQN model solves the job shop scheduling problem and determines the actions of multiple edge devices.

Because of the continuous characteristics of the IIoT, long short-term memory (LSTM) approaches, which can capture the pattern of time-series data, have been researched for the IIoT area. The LSTM-Gauss-NBayes method was proposed in [23] to detect outliers in IIoT. This method attempted to exploit the prediction capability of the LSTM model for time-series data and the classification performance of the Gaussian naive Bayes model to predict errors. In [24], the LSTM-based model forecasts the number of people given time and location at 15, 30, and 60 min intervals at the building and access points. Using appliance data collected by smart meters, Lai *et al.* proposed an LSTM-based edge-computing architecture that recognizes industrial electrical equipment [25].

In addition, recent RL-based MAC studies were conducted [26], [27], [28]. The authors assumed a divided timeslot in their schemes and presented an RL model to avoid transmission collisions between nodes. In these methods, DLMA nodes use the DRL architecture to learn the policy to maximize the sum throughput and transmission fairness. However, their technique is limited because it does not consider the deafness problem that occurs when using a directional antenna.

To the best of our knowledge, this is the first study on a directional MAC protocol using a machine learning approach to resolve the deafness problem in IIoT networks. The proposed algorithm attempts to predict whether the deafness problem will occur based on a machine learning technique.

III. Basic Assumption

A. Antenna Model

We assume that each IIoTD is equipped with switched beam antenna model and is divided into M sections. Each IIoTD activates one beam for transmission and reception and operates in omni-directional mode to detect signals in all directions during idle mode. During transmitting/receiving, the beams in the other directions are disabled, except for the used beam. That is, we assume that each IIoTD sends data to only one destination device. We assume that all IIoTDs have information about the beam pair used to communicate with other nodes. This information can be distributed during the initial network formation by the IIoTD management unit, such as edge or control management units [29].

B. Deafness problem

One of the significant issues in D2D communication between IIoTDs using directional antennas is deafness. The deafness problem causes significant performance degradation in terms of the latency and throughput of IIoT networks. The deafness problem occurs during the exchange of control frames in D2D communication. To perform D2D communication, the sending IIoTD transmits a DRTS frame in the direction of the target IIoTD. The IIoTD that receiv the DRTS responds by sending a DCTS frame in the direction of the sending IIoTD. After the exchange of DRTS and DCTS is completed, a beam pair was formed between the two IIoTDs to perform data communication. At this time, IIoTDs in communication cannot receive DRTS from other neighboring IIoTDs because they block antennas other than the antenna used for communication. As a result, the neighboring IIoTDs do not receive DCTSs and will continue to retransmit DRTS, which will lead to overall network performance degradation.

Fig. 1 shows the deafness problem in D2D communication between IIoTDs. As shown in the figure, because IIoTDs X and Y are in communication, antennas other than the antenna used for communication are blocked (antennas 1, 3, and 4 for IIoTD X and antennas 1, 2, and 3 for IIoTD Y, respectively). Therefore, DRTS frames from IIoTDs A and B cannot reach the target IIoTDs.

C. Beam table matrix

We assume a network with a total of N IIoTDs deployed and N_i denotes ith IIoTD ($0 \leq i < N$). Furthermore, we assume that each IIoTD is equipped with directional antennas were divided into M sectors. Let $\mathbf{B}_i$ denote the group of antenna beams for N_i. Then, $\mathbf{B}_i \in \{b_i^0, b_i^1, \cdots b_i^{M-1}\}$ where: b_i^j denotes the jth antenna for N_i. Let $\mathbf{I}_{i,k}$ denote the beam index used when N_i transmits to N_k. Each IIoTD should determine the transmitting antenna according to the target IIoTD location for communication. Thus, each IIoTD has a beam table-matrix ($\mathbb{M}$) with the information on the beam pair between all IIoTDs. $\mathbb{M}$ is given by:

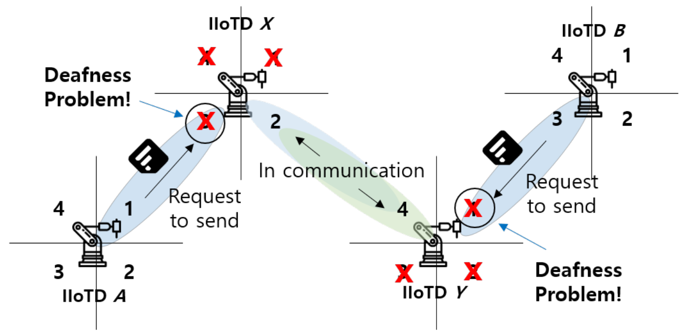


Fig. 1: Deafness problem in D2D communication (the number of antennas is 4).

$$\mathbb{M} = \begin{bmatrix} \mathbf{I}_{0,0} & \mathbf{I}_{0,1} & \cdots & \mathbf{I}_{0,N-1} \\ \mathbf{I}_{1,0} & \mathbf{I}_{1,1} & \cdots & \mathbf{I}_{1,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{I}_{N-1,0} & \mathbf{I}_{N-1,1} & \cdots & \mathbf{I}_{N-1,N-1} \end{bmatrix}. \tag{1}$$

D. Network failure

Traditionally, the reason why IIoTD cannot receive a signal is classified as 1) when the signal collides with interference or 2) when the signal strength is weakened due to path loss. However, in the mmWave band, attenuation of signals due to obstacles and the deafness problem mentioned in the previous subsection also occur. When a network failure occurs in the communication system, the damaged signal is restored or resolved by retransmission at the transmitting device. However, in the case of the deafness problem, the above method cannot be fundamentally solved, and there is only one method to schedule or avoid the deafness problem so that it does not occur. In D2D communication, scheduling is not possible owing to the randomness of the packet arrival. Therefore, in this study, we focused on recognizing and avoiding deafness.

E. Problem Formulation

To increase the overall throughput in IIoTD D2D networks, link scheduling to avoid collisions and deafness is one of the best solutions. In this subsection, we formulate a problem to calculate the theoretical optimal network throughput in D2D IIoTD networks.

We modeled our D2D IIoTD network using directed graph $G = (\mathbb{N}, \mathbb{E})$, where $\mathbb{N}$ represents the set of all IIoTDs and $\mathbb{E}$ is the set of all the directional edges. The set of IIoTDs and directional edges are represented by $\mathbb{N} = \{N_0, N_1, \ldots, N_{N-1}\}$ and $\mathbb{E} = \{E_0, E_1, \ldots, E_{E-1}\}$, where E denotes the number of edges. In addition, we denoted the set of edges' weights as:

$\mathbb{W} = \{W_0, W_1, \ldots, W_{E-1}\}$. The weight of edge E_i at time slot t, $W_i(t)$, is given by:

$$W_i(t) = A_i(t), \tag{2}$$

where $A_i(t)$ denotes the achievable rate of edge E_i at time slot t. $A_i(t)$ is defined as follows:

$$A_i(t) = B \log_2(1 + \frac{P_T G_T G_R (\frac{\lambda}{4\pi d})^2}{n_0 B + I}), \tag{3}$$

where B denotes the channel bandwidth of wireless link and n_0 is the noise power spectral density. I is the wireless interference and P_T is the IIoTD's transmitted power, d is the distance, and G_T and G_R are the directional beam gains, of transmitters IIoTD and IIoTD, respectively, λ is the wavelength of the beam [36].

Then, the objective function is designed to find a set of links that maximizes the sum of weights, as follows:

$$\text{maximize} \sum_{e \in \mathbb{E}} W_e(t) \cdot \mathbb{I}_e(t), \tag{4}$$

where $\mathbb{I}_e(t)$ is an indicator variable and it can be expressed as two cases

$$\mathbb{I}_i(t) = \begin{cases} 1, & \text{if } E_i \text{ can be scheduled on time slot } t, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

However, the problem of finding a link set that simply maximizes the weight is not feasible. The following constraints can be considered for collision and deafness: An IIoTD cannot simultaneously receive data through multiple incoming directional links. Therefore, to avoid collision/deafness among transmission nodes and ensure a feasible link scheduling scheme, we define the following feasible scheduling constraint:

$$\mathbb{I}_i^j(t) + \sum_{k \in N, i \neq k \neq j} \mathbb{I}_k^j(t) \leq 1, \tag{6}$$

where $\mathbb{I}_i^j(t)$ denotes the indicator variable whether node i sends a data to j at timeslot t. In addition, each IIoTD sends data to only one destination, and we define the following constraint.

$$\sum_{j \in N, j \neq i} \mathbb{I}_i^j(t) = 1. \tag{7}$$

The objective function (4) under this constraint is complex and requires a considerable amount of time to be solved using various solvers. However, link scheduling is limited because there is no central coordinator in contention-based MAC. In competition-based D2D communication, if the link is preempted, it is impossible to determine whether other IIoTDs have occupied the link. Thus, IIoTD should recognize the link state and avoid network failure. Therefore, in this study, we propose a technique to identify the cause of link failure using a deep-learning architecture and investigate the effectiveness of the proposed scheme compared with the solution of the designed objective function.

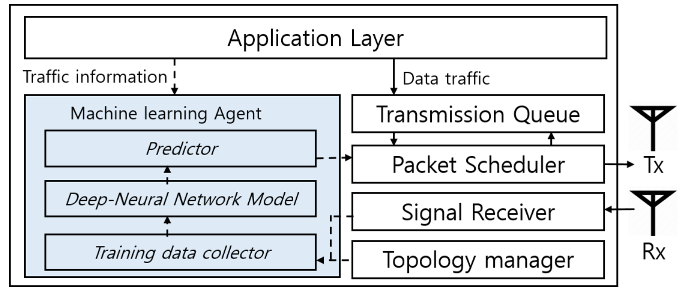


Fig. 2: System architecture of the proposed ML-DMAC scheme.

IV. Machine Learning-based Directional MAC

In this section, we describe machine learning-based directional MAC scheme to identify the deafness problem from network failures. We applied supervised deep learning to D2D IIoT networks. The our proposed machine learning-based DMAC (ML-DMAC) classifies network failures as follows:

- **Damaged signal**: the case where the signal is damaged due to obstacle, path-loss, interference, collision, or etc. In D2D communication, in this case, it is recommended to perform retransmission after backoff is performed at the sender.
- **Deafness problem**: the case that IIoTD in communication cannot hear the signal by blocking some antennas. Even if retransmission is performed, another approach is needed because it can still experience deafness.

By combining the above analysis, we establish the following hypothesis:

$$\begin{aligned} &H_f : \text{Network failure was caused by a damaged signal.} \\ &H_d : \text{Network failure was caused by a deafness problem.} \end{aligned} \tag{8}$$

Based on H_f and H_d, the proposed ML-DMAC determined appropriate actions when a network failure occurs.

Fig. 2 shows the system architecture of the proposed ML-DMAC scheme. The core part of the proposed system architecture is a *machine learning agent*. The machine learning agent consists of 1) a training data collector, 2) a Deep-Neural-Network model, and 3) a predictor. The functions of each component are as follows:

- **Training data collector**: It collects training data for decisions, specifically information on the result of communication (success/failure) based on parameters from the application layer, topology manager, and signal receiver.
- **Deep-Neural Network (DNN) model**: It is a DNN model from the collected information. As the communication is performed, the DNN model update is performed steadily.
- **Predictor**: Based on the results from the DNN model, it determines whether the signal is damaged, resulting in a network failure or deafness has occurred.

A. Training data set

To differentiate deafness from network failure, each node should be trained in a specific topology. To collect training data, we used an NS-3 simulator and the structure of the training data is as follows: sender/receiver index (N_i and N_j), transmitting beam index ($\mathbf{I}_{i,j}$), packet size ($|P|_i$), distance between the sender and receiver ($D_{i,j}$), number of neighboring nodes ($\mathbf{N}_{i,j}$), last ACK timeout (t_i^{ack}), number of retransmissions ($|R|_i$), and network failure label (y). In the NS-3 simulator, each sender recorded the training data when there was data to be sent. If the transmission was successful, the recorded information was deleted. However, if a network failure occurs, the label is recorded as deafness if the destination node is communicating, otherwise it is recorded as a damage signal.

B. Training DNN model

The transmission parameters identified in the previous section are the inputs, and hypothesis (8) is the output of the DNN model. The training process was based on a mini-batch gradient descent algorithm. Based on the training data set, the DNN model updates its weight parameters ($\mathbf{w_i}$) for multiple fully connected (FC) layers by minimizing the loss function. For the cost function of training, we consider the cross-entropy function, which is given by

$$C = -\sum_i y_i \log \tilde{y}_i + (1 - y_i)\log(1 - \tilde{y}_i) \tag{9}$$

where C, y_i, $\tilde{y}_i$ and i denote the entropy loss, actual output set for ith epoch, expected output set for ith epoch and iteration epochs, respectively. The output of each layer was passed to the adjacent layer using the softmax activation function [30]:

$$f(y_i) = \frac{e^{(y_i)}}{\sum_j e^{(y_j)}}. \tag{10}$$

Finally, the shape of the output y appears as a vector of the probabilities of H_d and H_f, that is, $y = \{P(H_d), P(H_f)\}$ where $P(H_d)$ and $P(H_f)$ denote the probability of deafness, and link failure, respectively. Since the output data format is a vector of probabilities, the machine learning agent uses a one-hot encoder to create a vector of 0 or 1.

Using the gradient descent method, the weight $\mathbf{w_i}$ is updated as $\mathbf{w_i}' = \mathbf{w_i} - \alpha \frac{\partial C}{\partial \mathbf{w_i}}$, where α denotes the learning rate of the DNN. The DNN model was initialized based on the data generated for approximately 100 s after the network topology was set. The DNN model was continuously updated in real-time to increase prediction accuracy.

Fig. 3 shows the designed DNN architecture. Our deep-learning model has up to 8 levels and each layer generates 128 outputs and we used the Xavier and Kaiming initializer [31], [32]. In addition, dropout was applied to prevent over-fitting [33] and the Adam optimizer [34] was used to minimize the loss function.

Tables I and II show the prediction accuracies of the proposed deep learning architecture. For learning, each node generated approximately 1Mbps of data traffic and collected data 20 s after the start of the simulation in grid topology.

In addition, to evaluate the generalization ability of the proposed machine learning model, we measured the prediction accuracy of our proposed model in random deployment scenario. As shown in the table, the maximum prediction accuracy of the proposed method was 98.3%. Note that when a node experiences a DCTS timeout, it can be distinguished by about 97.2-98.3%, In addition, when an experiment was performed based on previously learned data in a random deployment scenario, performance degradation of about 10-15% was confirmed. This is because some training data acted as noise due to the change of the location. Interestingly, as the number of network layers increases, the prediction accuracy does not increase, and it exhibits the highest accuracy when the number of layers is two or four. In addition, when the number of nodes is relatively small, the prediction accuracy

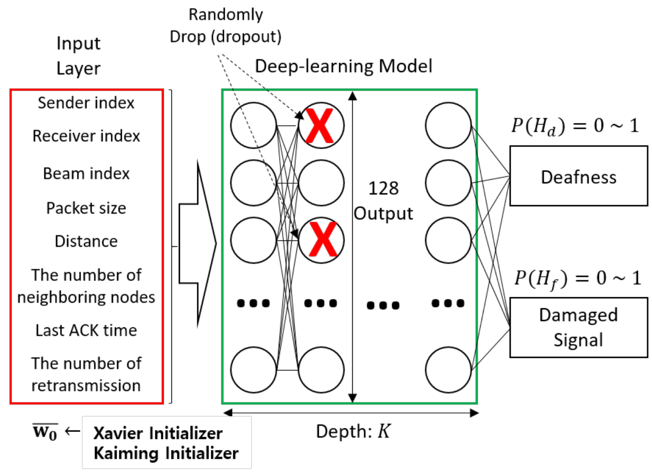


Fig. 3: Proposed deep-learning architecture.

TABLE I: Deafness prediction accuracy (Layer=8).

	nodes=5	nodes=10	nodes=15	nodes=20
Predication Accuracy (Only DNN)	67%	78%	86%	**96.5%**
Predication Accuracy (Xavier Initializer)	68.3%	77.6%	86.8%	**95.4%**
Predication Accuracy (Kaiming Initializer)	68.5%	77.4%	85.9%	**95.7%**
Predication Accuracy (Dropout)	67.3%	78.3%	85.3%	**96.2%**
Predication Accuracy (Xavier, dropout)	68.5%	79.1%	87.6%	**97.5%**
Predication Accuracy (Kaiming, Dropout)	68.8%	80.2%	88.1%	**97.4%**
Predication Accuracy (Random Scenario)	55.8%	71.2%	75.1%	**84.4%**

TABLE II: Deafness prediction accuracy (# of nodes=20).

	Layer=1	Layer=2	Layer=4	Layer=8
Predication Accuracy (Only DNN)	93.2%	95.1%	**97.2%**	96.5%
Predication Accuracy (Xavier Initializer)	94.1%	95.7%	**96.2%**	95.4%
Predication Accuracy (Kaiming Initializer)	94.2%	95.3%	**96.4%**	95.7%
Predication Accuracy (Dropout)	93.2%	**97.3%**	95.1%	96.2%
Predication Accuracy (Xavier, dropout)	93.7%	**98.1%**	96.7%	97.5%
Predication Accuracy (Kaiming, Dropout)	94.1%	**98.3%**	96.5%	97.4%
Predication Accuracy (Random Scenario)	81.1%	**88.1%**	86.4%	87.7%

Algorithm 1: The algorithm of ML-DMAC

1 ML-DMAC D2D communication procedure:
2 DCTS timeout occurs:
3 **begin**
4 $\quad g \leftarrow [N_i, N_j, \mathbf{I}_{i,j}, |P|_i, D_{i,j}, \mathbf{N}_{i,j}, t_i^{ack}, |R|_i]$;
$\quad$ /* g: input array of DNN */
5 $\quad y \leftarrow predict(g)$; /* $y = [\mathbf{H}_f, \mathbf{H}_d]$ */
6 $\quad y' \leftarrow one-hot(y)$; /* $y' = [0,1]$ or $[1,0]$ */
8 $\quad$ **if** $\mathbf{H}_f == 1$ /* damaged signal case */ **then**
9 $\quad\quad CW_{max} \leftarrow CW_{cur} * 2$;
10 $\quad\quad$ Back-off and retransmission of the DRTS;
11 $\quad$ **else if** $\mathbf{H}_d == 1$ /* deafness case */ **then**
12 $\quad\quad$ Delay transmission;
13 $\quad\quad$ Queue scheduling;
14 **end**

is small. It was found that the prediction accuracy was low owing to insufficient training data, and if the network training time was increased, it was expected to show high accuracy.

C. DNN-based D2D communication

Using the trained DNN model, the sender can determine whether the cause of the network failure is a damaged signal or deafness. Algorithm 1 shows the operation process of the proposed ML-DMAC. If a DCTS timeout occurs, the sender queries the trained DNN model for the cause of network failure with the input parameters used for DRTS transmission. First, when DCTS timeout occurs, the ML agent predicts the cause of network failure through the DNN model (*lines* 4-6). If it is determined that the cause of network failure is a damaged signal, retransmission is performed by exponentially increasing the backoff window size (*lines* 7–9). However, instead of performing retransmission, it checks its transmission queue and communicates with other nodes (*lines* 10–12)[2]. Fig. 4 shows an example of this process. We assume that node A has data frames to transmit in the order of destination nodes B, C, D, and C in the transmission queue. To transmit the data frame to node B, node A transmits a DRTS frame to node B (Fig. 4a). Because node B communicates with node D, node B cannot receive the DRTS frame from node A. Consequently, node A received a DCTS timeout event (Fig. 4b). To determine whether this network failure is caused by a damaged signal or a deafness problem, node A queries the trained DNN model with its current state information. From Fig. 4c, deafness is predicted by the DNN model. Node A then tries to locate the data frame in the transmission queue, whose destination is in a different antenna direction from node B. Since node C is in a different direction from node B, node A transmits the DRTS to node C to transmit the frame to node C, as depicted in Fig. 4d. The previous frame destined for node B is queued to node A's transmission queue.

[2]It should communicate with a node that is not in the direction of the antenna that was used for DRTS transmission previously.

TABLE III: Simulation parameters.

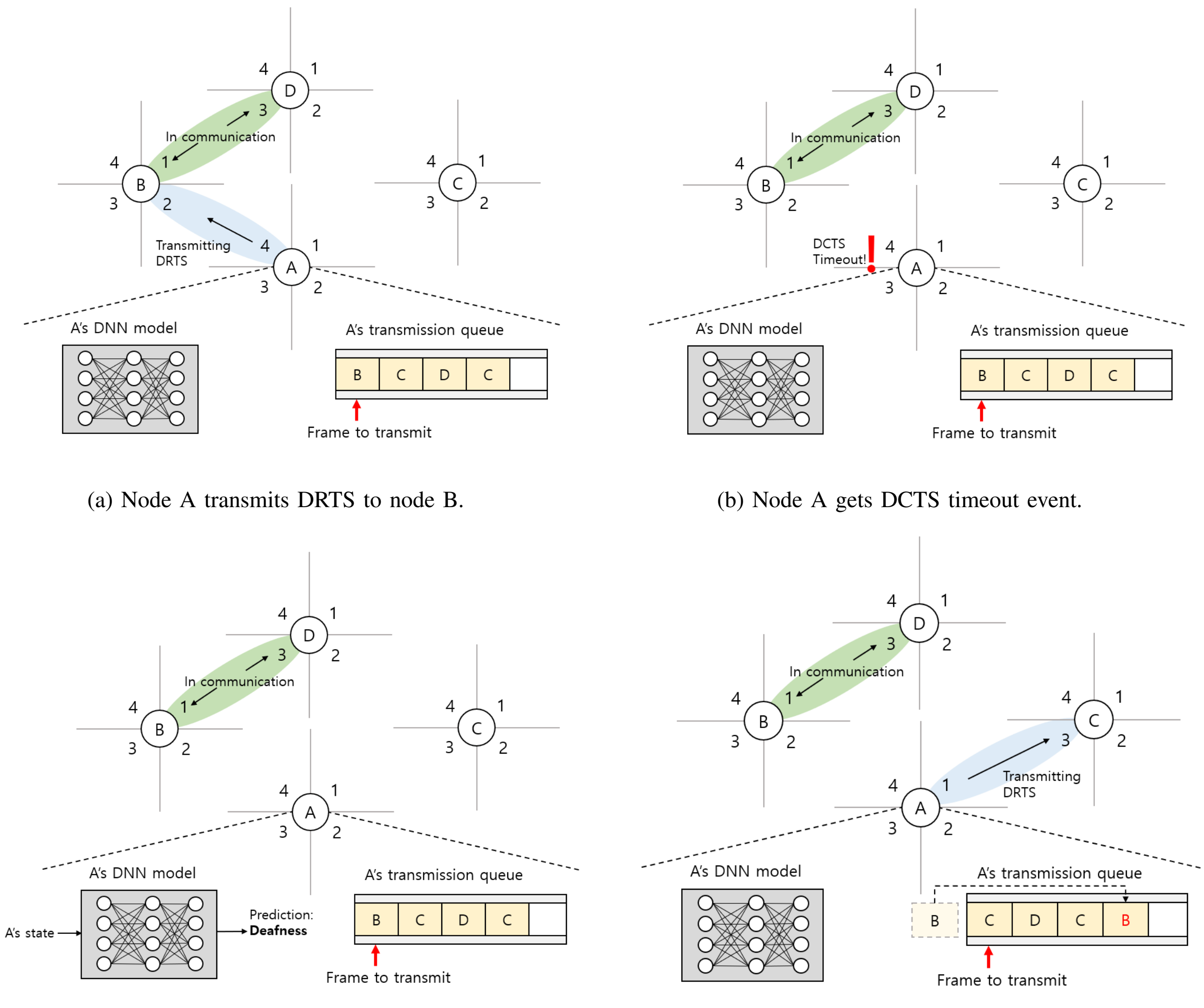
Simulation parameter	Value
Transmit power	15 dBm
Receive sensitivity	-55 dBm
The number of antennas	6
The degree of each antenna	$\pi/3$ (radian)
Packet size	1400 bytes
Data rate of transmission channel	54 Mbps
CWmin	16
CWmax	1024
The number of nodes	9, 16, 25, 36, 49
Simulation duration	100 s

V. Performance Evaluation

The performance of the proposed scheme was evaluated using an NS-3 simulation tool. NS-3 simulator based on C++/Phyton and our proposed machine learning model-based in Python were implemented independently. To ensure compatibility between the two modules, an object used for referencing an external Python module was placed in the NS-3. In our simulator, when a problem occurs in a link, the node object calls *getMacParameter()* and *getPhyParameter()* to obtain the input parameters (N_i, N_j, $\mathbf{I}_{i,j}$, $|P|_i$, $D_{i,j}$, $\mathbf{N}_{i,j}$, t_i^{ack}, and $|R|_i$). Subsequently, it passes the input parameters to the external machine learning model and receives the machine learning prediction result (y). ML-DMAC was compared with DMAC [7], circular RTS, CTS MAC (CRCM) [12], and AL-DMAC [35]. DMAC uses the DRTS/DCTS/DDATA/DACK transactions to exchange data. The communication processes between DMAC and ML-DMAC are the same, except for the proposed ML-based directional MAC scheme. CRCM uses CRTS/CCTS/DDATA/DACK transactions to exchange data. DRTS and DCTS are sequentially transmitted in every direction for every transaction. In addition, AL-DMAC is designed to increase the overall network throughput based on the deep reinforcement learning technique.

In our simulation scenario, we assumed grid and random deployment scenarios. In the grid scenario, each node sends data to adjacent nodes in the up, down, left, and right directions. Therefore, each node can have at most four data-flows. For example, Fig. 5 shows the grid deployment when the number of nodes was 16. In the random deployment scenario, nodes were randomly deployed in a 100 m $\times$ 100 m square area with a uniform distribution. In addition, to evaluate the generalization ability of the proposed machine learning model, a machine learning agent trained in a grid topology is utilized in random deployment scenario. Since IIoTDs in industrial systems are usually fixed at their positions, mobility is not considered in simulation scenarios. The simulation parameters are listed in Table III. The following performance metrics were considered during the simulation:

- **Throughput** is defined as total received data traffic in bits transferred successfully from all nodes divided by time.
- **Deafness duration** is defined as the time difference between the first RTS transmission and CTS reception. Deafness duration is averaged over the number of RTS/CTS transactions.



(a) Node A transmits DRTS to node B.

(b) Node A gets DCTS timeout event.

(c) Deafness state is predicted by trained DNN model.

(d) Node A transmits DRTS to node C.

Fig. 4: Example scenario of ML-DMAC process.

- **Jain's fairness index** is defined as squared mean of x_i over the mean of x_i^2, formulated as

$$J(x_1, x_2, \cdots, x_N) = \frac{\left(\sum_{i=1}^{N} x_i\right)^2}{N \sum_{i=1}^{N} x_i^2} \tag{11}$$

where N is the number of nodes, and x_i is the throughput of ith node.

Figs. 6 and 7 show the results of the performance evaluation of the data flow rate. Three MAC protocols were evaluated using grid and random deployment scenarios. The number of nodes was 36 for both grid and random deployment scenarios. The data rate of the data flow varied from 1000 Kbps to 2000 Kbps with an interval of 200 Kbps. The other simulation parameters are listed in Table III. The throughput of ML-DMAC is greater than that of DMAC by 13.4%-31.4% and that of CRCM by 19.9%-60.0% in both scenarios. ML-DMAC can resolve the deafness problem by recognizing whether a node is in a deafness state using a trained DNN model. CRCM shows the smaller throughput than other protocols, since CRTS/CCTS mechanism generates significant communication overhead. In addition, ML-DMAC shows a performance improvement of approximately 10-20% compared to AL-DMAC which is based on reinforcement learning. Even if AL-DMAC attempts to transmit a data in a direction with a good channel condition, there is no technique to recognize and avoid deafness when it occurs. As a result, when deafness occurred, the number of retransmission attempts increased, resulting in a loss of throughput.

From the Fig. 7, the deafness duration of the ML-DMAC was the shortest among the three protocols. The ML-DMAC reduces the deafness duration by transmitting it to another beam direction when deafness is recognized. The deafness duration of CRCM was much longer than that of the other protocols. This is because the CRTS/CCTS/DDATA/DACK transactions are longer than DRTS/DCTS/DDATA/DACK transactions.

A performance evaluation was conducted with a varying number of nodes in the grid and random deployment scenarios.

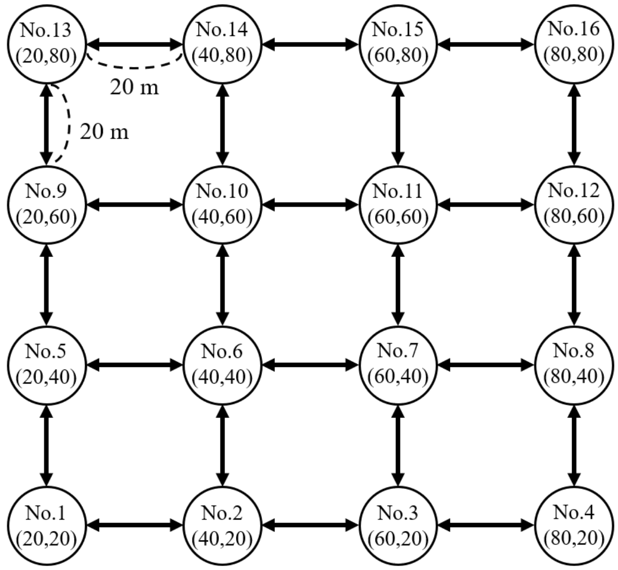


Fig. 5: Deployment for grid deployment scenario when the number of nodes is 16.

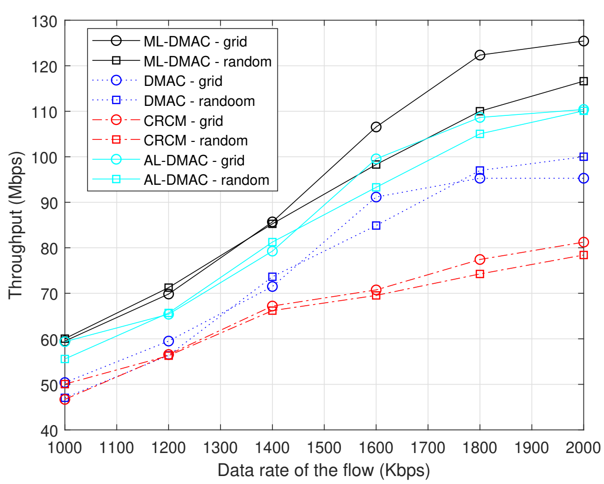


Fig. 6: Throughput over the data rate of the data flow.

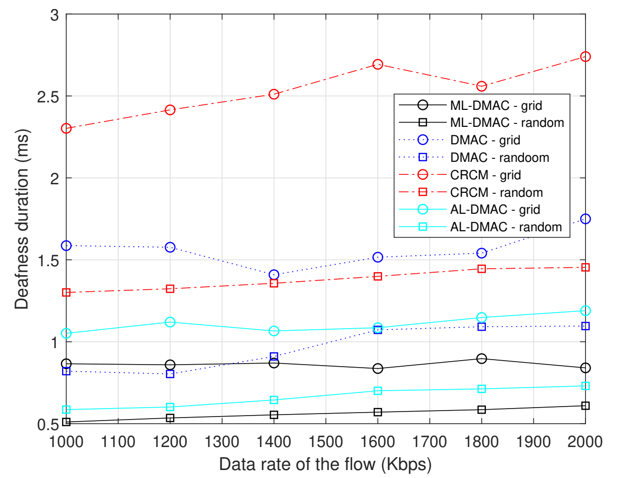


Fig. 7: Deafness duration over the data rate of the data flow.

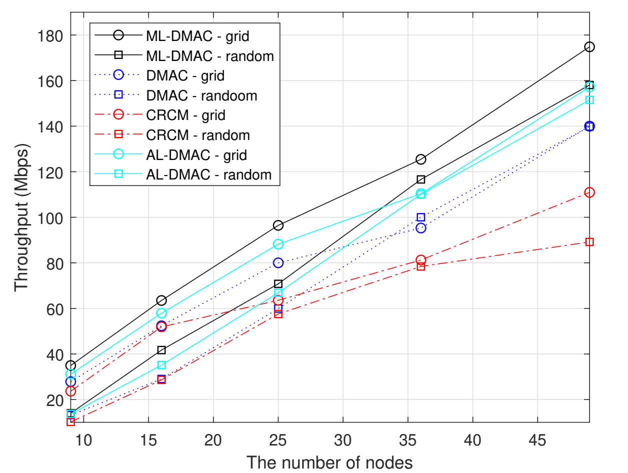


Fig. 8: Throughput over the number of nodes.

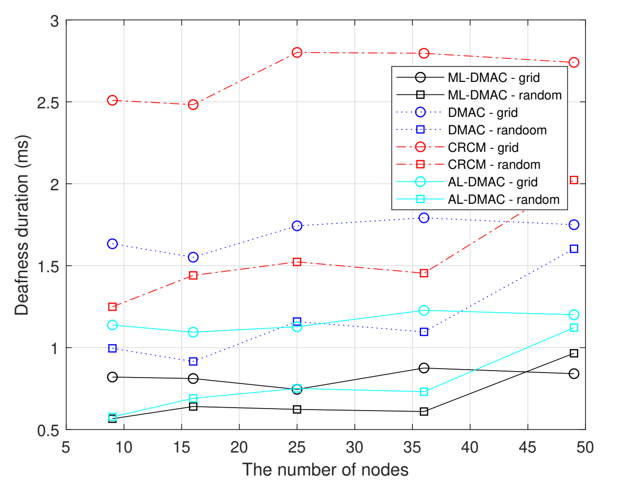


Fig. 9: Deafness duration over the number of nodes.

The data flow rate was 2000 Kbps. The number of nodes varied from 9 to 49. As the number of nodes increases, the node and traffic densities increase. Figs. 8 and 9 show the results of the performance evaluation based on the number of nodes. From the Fig. 8, ML-DMAC exhibits the highest throughput compared with DMAC and CRCM. The throughput of ML-DMAC was greater than that of DMAC by 6.2%-43.7%, that of CRCM by 19.9%-77.3%, and that of AL-DMAC by 5%-11% in both scenarios. The reasons for this were two fold. First, ML-DMAC can capture the deafness event; therefore, ML-DMAC nodes can avoid the deafness problem and reschedule the transmission to another antenna direction. Second, as the number of nodes increases, the ratio of traffic-intensive nodes also increases, which makes the deafness problem worse. Fig. 9 shows the deafness duration for carious numbers of nodes. Similar to Fig. 7, the deafness duration of ML-DMAC was the smallest, and that of CRCM was the greatest for every scenario.

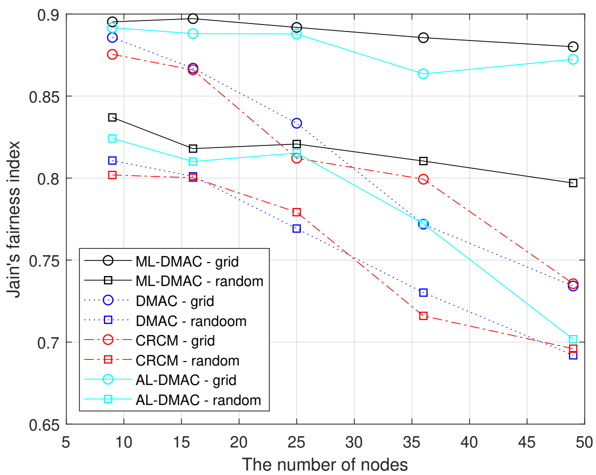


Fig. 10: Jane's fairness index over the number of nodes in grid deployment scenario.

Fig. 10 shows Jane's fairness index with varying numbers of nodes in both deployment scenarios when the number of nodes is 36, and the rate of the date flow is 2000 Kbps. Jane's fairness index in the grid deployment scenario tends to be greater than that in the random deployment scenario because the random deployment scenario has a large variance in the number of data flows per node. ML-DMAC shows the highest Jane's fairness index compared to DMAC and CRCM. The difference between Jane's fairness index of ML-DMAC and that of other protocols increases with increasing nodes. As the number of nodes and traffic density increase, at specific node will likely occupy the channel once it begins transmission. Since ML-DMAC can recognize deafness and try to transmit through another beam direction, instead of waiting for the end of the communication transaction, each node is likely to have a higher probability of transmitting data.

Consequently, ML-DMAC showed the best performance in throughput, deafness duration, and Jane's fairness index. The proposed scheme improves the performance with directional MAC by effectively resolving the deafness problem in IIoT system. In addition, the grid deployment scenario performed better on average than the random deployment scenario. This is because, when a node is placed in a random location, spatial reuse is not possible. Therefore, in order to improve the overall system performance of the IIoTD, it is best to arrange it to maximize spatial reuse.

VI. Conclusion

In this study we propose an ML-based directional MAC for IIoT networks. The proposed technique resolves the deafness problem without additional communication overhead by using a DNN approach. DNN model tries to distinguish deafness from the damaged signal when a network failure occurs. By recognizing the deafness state with the trained DNN model, the transmitting node can avoid deafness and reschedule the transmission through another beam direction. Throughout the performance analysis, ML-DMAC was evaluated with DMAC and CRCM in grid and random deployment scenarios. ML-DMAC outperformed the the existing comparison protocols in throughput, deafness duration, and Jane's fairness index. In future work, we will consider another deep learning-based approach, such as LSTM and DRL, for better performance in IIoT networks. Another direction is to study the directional MAC protocol for high mobility networks, which should consider the frequently changing beam direction of the receiving node.

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