Autonomous Decentralized Transmission Timing Control in Wireless Sensor Network

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***Abstract*—In recent years, with the development of Internet-of-things (IoT) and machine-to-machine (M2M) communication, low power wide area (LPWA) networks have attracted attention. LPWA generally adopts a pure ALOHA protocol as the MAC layer access protocol to reduce the wireless device cost. If multiple wireless devices simultaneously transmit packets, a packet collision happens at a fusion center (FC) that collects wireless devices' information. To avoid such collision, the FC may control the wireless devices' transmission timings in a centralized manner. However, this requires control signal exchanges, resulting in increased communication overhead and increased battery consumption. In this paper, we propose a method to avoid packet collisions. The proposed method consists of two steps. Firstly, the transmission start timing of each device is autonomously set by reinforcement learning. Then, the transmission probability is determined based on the transmission start delay time. The computer simulation results show that the proposed method can improve the average packet delivery rate (PDR) by 42% compared to the conventional ALOHA protocol.**

I. Introduction

With the advancement of the Internet-of-things (IoT) and machine to machine (M2M) communications [1], low power wide area network (LPWAN) such as long range wide area network (LoRaWAN) is attracting attention [2]. LoRaWAN adopts the chirp spread spectrum (CSS) as a physical layer modulation scheme [3].

At the medium access control (MAC) layer, LoRaWAN generally adopts asynchronous random access protocols such as pure ALOHA protocol while considering duty-cycle (DC) [4]. This simple access protocol may degrade the communication quality due to packet collision when a large number of wireless devices share the wireless resources. One of the causes of packet collision has been burst traffic, in which a large number of wireless devices send the event packets at the same time due to event observation [5]. The application of carrier sense multiple access/collision avoidance (CSMA/CA) and the appropriate spreading factor assignment have been investigated to avoid simulatnaous packet transmission [6][7]. However, these methods had problems such as battery consumption due to carrier sense (CS), hidden device problems, and overhead caused by control signals. Most of the existing works on wireless resource allocation assumed a static environment and relied on a formulated mathematical model [8]. Recent work on wireless resource allocation adopts model-independent reinforcement learning of a system environment [9] [10].

This paper proposes an autonomous decentralized transmission timing control for wireless devices using Q-learning to avoid packet collision in burst traffic environments. The proposed method consists of two steps. Firstly, each wireless device autonomously sets transmission start delay time by reinforcement learning. The different transmission timings of event packets can effectively reduce the packet collision probability. Secondly, each wireless device determines a transmission probability based on the transmission start delay time. When the same event is detected, each wireless device transmits highly correlated data, so there is little need for all the wireless devices to transmit packets to a fusion center (FC). Controlling the transmission probability of wireless devices can reduce the packet collision probability. The computer simulation results show that the proposed method can improve the average packet delivery rate (PDR) by 42% compared to the conventional ALOHA protocol.

The rest of this paper is organized as follows. In Sect. II, the LoRaWAN system model considered in this paper is introduced. In Sect. III, the autonomous decentralized transmission timing control is proposed. In Sect. IV, computer simulation results are provided to show the effectiveness of the proposed method. Sect. VI concludes the paper.

II. System Model

We consider the LoRaWAN based system in this paper. N LoRaWAN devices are randomly and uniformly distributed within a communication area of $D \times D$ [km^2]. Let us denote the set of LoRaWAN devices as $\mathcal{N} = \{n_0, n_1, \cdots, n_{N-1}\}$. All LoRaWAN devices are assumed to use the same spreading factors (SF). One FC that receives data from LoRaWAN devices is located at the center of the communication area.

A. Channel Model

In this paper, pathloss and shadowing loss are considered for a channel model. The received signal power of LoRaWAN device n at FC is given as

$$P_{\mathrm{r},n} = P_{\mathrm{t}} - P_{\mathrm{pl}}(d_n) - \psi, \tag{1}$$

where P_{t} [dB] is common transmit power for all LoRaWAN device, ψ [dB] is a shadowing component following a log-normal distribution. From [11], pathloss is given as

$$P_{\mathrm{pl}}(d_n) = 10a \log_{10} d_n + b + 10c \log_{10} f_{\mathrm{c}}, \tag{2}$$

where d_n [km] is the distance between LoRaWAN device n and FC, propagation parameters a, b, c are the pathloss coefficient, offset, and frequency loss component, respectively, f_c [MHz] is the carrier frequency.

The signal-to-noise power ratio (SNR) and the signal-to-interference power ratio (SIR) for LoRaWAN device n are calculated as

$$\begin{cases} \gamma_{\mathrm{SNR},n} &= P_{\mathrm{r},n} - \left(N_0 + 10\log_{10} W_\mathrm{b}\right) \\ \gamma_{\mathrm{SIR},n} &= P_{\mathrm{r},n} - \sum_{i\in\mathcal{I}} P_{\mathrm{r},i}, \end{cases} \tag{3}$$

where N_0 [dBm/Hz] is noise power spectrum density, W_b [Hz] is the frequency bandwith, $\mathcal{I}$ is the set of interfering LoRaWAN devices. When received signal satisfies both SNR thresholds Γ_{SNR} and SIR thresholds Γ_{SIR} at FC, the packet is considered to be successfully received [9] [12].

B. Event Generation and Detection

The event's location is randomly determined when it first occurs. Subsequently, the event occurs at the same position at a random time. The event propagates with speed V [m/s] outwards in a circle. LoRaWAN device n detects the event with the probability of δ_n, which is given by [5]

$$\delta_n = e^{-\alpha d_{\mathrm{e},n}}, \tag{4}$$

where α is the event propagation coefficient, $d_{\mathrm{e},n}$ [m] is a distance between LoRaWAN device n and the event epicenter. The event generates event true data $x \in [x_{\min}, x_{\max}]$, where $x_{\min}$ and $x_{\max}$ are the minimum and the maximum event true data, respectively. LoRaWAN device n observes sensing data x_n^{sens}, which is the event true data collapsed by the error. The sensing data, x_n^{sens}, is given by

$$x_n^{\mathrm{sens}} = x + e_n, \tag{5}$$

where $e_n \sim \mathcal{N}(0, 1)$.

C. Packet

This paper assumes that a packet consists of sensing data and basic data. Basic data includes LoRaWAN device identification information. The sensing data, x_n^{sens}, is quantized before transmission. Each LoRaWAN device generates two types of packets: a regular packet and an event packet. The regular packet is generated following a predetermined packet generation interval G_p[sec] and an event packet. The generation time of the regular packet at LoRaWAN device n, $T_{\mathrm{offset},n}$ is determined from the random number generated according to $\mathcal{U}(0, G_\mathrm{p})$. Second, the event packet is generated by event detection. Both packets have the equal packet length. The sensing data, x_n^{sens}, is linearly quantized with a predetermined number of quantization bit size Z and is converted into event transmission data $\hat{x}_n$ before transmission. The number of quantization levels, I, is $I = 2^Z$, which yields a quantized step size Δx_Z. The quantized representative value set is represented as $\mathcal{Z} = \left\{x_{Z,0}, x_{Z,1}, x_{Z,2}, \cdots, x_{Z,I-1}\right\}$. The elements of set $\mathcal{Z}$ are given as

$$x_{Z,i} = \begin{cases} x_{\min} + \Delta x_Z & (i = 0) \\ x_{Z,i-1} + \Delta x_Z & (\text{otherwise}) \end{cases}, \tag{6}$$

Event transmission data $\hat{x}_n$ is given as

$$\hat{x}_n = x_{Z,i^\star}, \tag{7}$$

where

$$i^\star = \arg\min_{0\le i<I} \left|x_n^{\mathrm{sens}} - x_{Z,i}\right|. \tag{8}$$

D. Packet Transmission

Packet size P_L [bit] is given as

$$P_\mathrm{L} = B_\mathrm{L} + Z, \tag{9}$$

where B_L [bit] is basic data size. Let us denote the SF of LoRaWAN devices by S. One CSS symbol can transmit S bit. Therefore, number of CSS symbols N_S required per packet is given as

$$N_\mathrm{S} = \lceil P_\mathrm{L}/S \rceil, \tag{10}$$

where $\lceil x \rceil$ returns the smallest integer larger than or equal to x. Symbol length T_S [sec] is given as

$$T_\mathrm{S} = \frac{W_\mathrm{b}}{2^S}. \tag{11}$$

The period from the start of the packet transmission to its completion is defined as a transmission phase. If a new packet is generated during the transmission phase, the LoRaWAN device stores the packet in its buffer. After the end of the transmission phase, each LoRaWAN device should wait for at least T_{DC} [sec] before starting new packet transmission. T_{DC} given as

$$T_{\mathrm{DC}} = \left(\frac{1 - D_\mathrm{c}}{D_\mathrm{c}}\right) N_\mathrm{S} T_\mathrm{S} \tag{12}$$

where $D_\mathrm{c} \in (0, 1]$ is the DC.

A regular packet is transmitted as an unconfirmed message that does not require an acknowledgment (ACK) signal from FC. By contrast, an event packet is sent as a confirmed message that requires an ACK signal from FC. If an event packet is successfully received by FC, the ACK signal is assumed to be ideally received by its sender LoRaWAN device.

III. Proposed Scheme

This section describes the adaptive allocation of transmission delay time using reinforcement learning and the reduction of the number of transmission devices by the event packet transmission probability.

A. Adaptive Allocation by Q-learning

1) Transmission Delay Time: In the proposed approach, each LoRaWAN device waits for a transmission delay time before it starts event packet transmission. This can reduce the packet collision probability. The transmission delay time for LoRaWAN device n is denoted by $t_n^{\mathrm{back}} \sim \mathcal{U}(0, W)$ with W being the DW size.

2) Learning Model: Q-learning is adopted to autonomously set the adaptive allocation of DW size. Q-learning is a model-free reinforcement learning algorithm. All LoRaWAN device install an agent of Q-learning. An agent observes its state such as current DW size and acts to maintain or change the DW size based on its observed information. In this paper, one epoch is defined as

(i) Each LoRaWAN device determines its own DW size.
(ii) The event occurs and the device detects it.
(iii) After waiting for t^{back}, the event packet is transmitted.
(iv) Determination of successful reception of event packets at FC.
(v) Reward calculation and Q-value update at each LoRaWAN device.

Let us define set of state $\mathcal{W}$ and set of action $\mathcal{A}$ in Q-learning as follows.

- Set of state $\mathcal{W}$: The set of available DW sizes of LoRaWAN device n. The elements are denoted by $\mathcal{W} = \{W_0, W_1, \ldots, W_{J-1}\}$, where J is the number of available DW sizes.
- Set of action $\mathcal{A}$: The set of changes of DW size. The elements are denoted by $\mathcal{A} = \{1, 0, -1\}$, where $1, 0, -1$ means larger, keep and smaller the DW size, respectively.

The agent of LoRaWAN device n is defined as

- State $s_{n,t} \in \mathcal{W}$: DW size of device n observed by the agent in epoch t
- Action $a_{n,t} \in \mathcal{A}$: DW size change in epoch t made by the agent.
- Reward $r_{n,t}$: Reward value for action $a_{n,t}$ in epoch t.
- Q value $Q\left(s_{n,t}, a_{n,t}\right)$: Value of action $a_{n,t}$ at state $s_{n,t}$.

Then, the Q-value is updated as

$$E^{\text{TD}}_{n,t} = r_{n,t+1} + \beta \left(\max_{a' \in \mathcal{A}(s_{t+1})} Q(s_{n,t+1}, a') - Q\left(s_{n,t}, a_{n,t}\right) \right), \tag{13}$$

$$Q\left(s_{n,t}, a_{n,t}\right) \leftarrow Q\left(s_{n,t}, a_{n,t}\right) + \eta E^{\text{TD}}_{n,t}, \tag{14}$$

where $E^{\text{TD}}_{n,t}$ is a temporal difference error, β is a discount rate, and η is a Q-learning rate. Since we adopt ϵ-greedy algorithm, $\epsilon(t)$ is given as

$$\epsilon(t) = 1 - \frac{t}{T}, \tag{15}$$

where T is the number of epochs.

3) Designing Reward values: Since Q-learning maximizes the sum of rewards, learning results depend on the reward design. There are three possible metrics for a reward function. The first metric is the reception of the ACK signal. The ACK reception indicates whether the FC successfully received the event packet. The second metric is transmission delay time $t_{\text{back},n}$, which represents the delay between an event's occurrence and its detection at the FC. The last metric is the number of transmission failures representing the failure rate at a specific DW size. For event detection, the event packet delivery rate should be high. In addition, the delay should be short. Accordingly, this paper proposes reward functions considering the ACK reception, transmission delay time, and the number of transmission failures.

The first reward considering the reception of the ACK signal only is given as

$$r^{\text{ack}}_{n,t} = \begin{cases} 1 & \text{if ACK is received} \\ -1 & \text{otherwise} \end{cases}. \tag{16}$$

The use of $r^{\text{ack}}_{n,t}$ may increase the probability of large detection delay at the FC because devices preferably select larger DW size to reduce packet collision. The second reward aiming at shorting the event detection delay is given by

$$r^{\text{delay}}_{n,t} = \begin{cases} 1 - \frac{t^{\text{back}}_n}{\max_{W \in \mathcal{W}} W} & \text{if ACK is received} \\ -1 & \text{otherwise} \end{cases}, \tag{17}$$

$$r^{\text{more delay}}_{n,t} = \begin{cases} 1 - \frac{t^{\text{back}}_n}{\max_{W \in \mathcal{W}} W} & \text{if ACK is received} \\ -\frac{t^{\text{back}}_n}{\max_{W \in \mathcal{W}} W} & \text{otherwise} \end{cases}, \tag{18}$$

The third reward considering the number of transmission failures to packet collision is given by

$$r^{\text{fail}}_{n,t} = \begin{cases} 1 & \text{if ACK is received} \\ -\frac{N^{\text{fail}}_{n,j}}{N^{\text{fail}}_{\text{all},n}} & \text{otherwise} \end{cases}, \tag{19}$$

$$r^{\text{fail\&delay}}_{n,t} = \begin{cases} 1 - \frac{t^{\text{back}}_n}{\max_{W \in \mathcal{W}} W} & \text{if ACK is received} \\ -\frac{N^{\text{fail}}_{n,j}}{N^{\text{fail}}_{\text{all},n}} & \text{otherwise} \end{cases}, \tag{20}$$

where $N^{\text{fail}}_{\text{all},n}$ is the total number of failed event packet transmitted from device n.

B. Event Packet Transmission Probability

When multiple devices observe the same event, they may transmit event packets simultaneously, which results in packet collision. To avoid this collision, an event packet transmission probability $p_{\text{s},n} \in (0, 1]$ is introduced to LoRaWAN device n as shown in Fig. 1. By introducing the event packet transmission probability, some LoRaWAN devices do not transmit event packets. As a result, the number of LoRaWAN devices simultaneously transmitting packet can be reduced. This can reduce the collision probability of event packets.

Event packet transmission probability $p_{\text{s},n}$ is dynamically controlled by transmission delay time t^{back}_n as

$$p_{\text{s},n} = -\log \left(\frac{t^{\text{back}}_n}{W_t} \right). \tag{21}$$

By reducing the transmission probability for long transmission delay time t^{back}_n, the probability for the event packets already being transmitted is corrupted by the new event packets can be reduced. In addition, event packet transmission probability $p_{\text{s},n}$ becomes high, and when the t^{back}_n is long, $p_{\text{s},n}$ becomes low, as shown in Fig.2. The rationale behind this setting is as follows: the probability of all LoRaWAN devices does not transmit reduce because function $-\log()$ has a region where the probability meets 1.

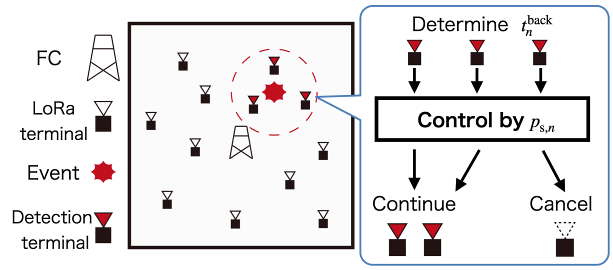


Fig. 1. Reduction of number of transmit devices by $p_{s,n}$

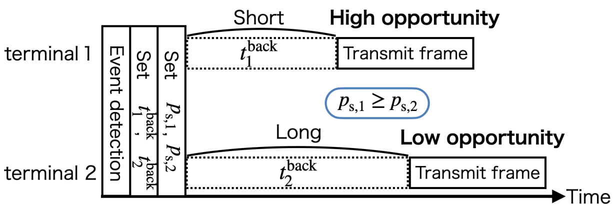


Fig. 2. Changes in $p_{s,n}$

IV. Simulation Results

Table I shows the simulation parameters. The parameters of LoRaWAN are following Japanese parameter configuration AS923 [4]. Table II shows the learning parameters.

A. Evaluation Criteria

The event packet delivery rate (PDR) defined as

$$\text{PDR} = R/S_{\text{P}}, \tag{22}$$

where R is the number of event packets successfully received and S_{P} is the number of event packets transmitted from devices.

Let $\mathcal{R}$ denote the set of LoRaWAN devices whose event packet is successfully received by the FC. The FC averages the received values to derive the estimate of the true event value. The squared error between the estimate of the true event value and the true event value is calculated as

$$E_Z \triangleq \left(\frac{1}{|\mathcal{R}|} \sum_{k \in \mathcal{R}} \hat{y}_k - x \right)^2, \tag{23}$$

where $\hat{y}_k$ is the received value from LoRaWAN device $k \in \mathcal{R}$.

The detection delay, t_n^{R}, of LoRaWAN device n is defined as

$$t_n^{\text{R}} = \frac{d_{\text{e},n}}{V} + T_{\text{S}} N_{\text{S}}. \tag{24}$$

For simplicity, this paper does not consider the processing time of packet generation, transmission, and reception. The shortest detection time at the FC is defined as

$$t_{\text{m}} = \min_{n \in \mathcal{N}} t_n^{\text{R}} - t_{\text{o}}, \tag{25}$$

where t_{o} is event occurrence time.

The event detection probability at the FC is calculated as the ratio between the number of events successfully detected by the FC and the total number of events. If at least one event packet is successfully received by the FC, we consider that the event is detected.

TABLE I
SIMULATION PARAMETER

Simulation area $D \times D$	1×1 [km^2]
Simulation time	10 [min]
Number of LoRaWAN devices N	500
Transmit power P_{t}	13 [dBm]
Carrier frequency f_{c}	923 [MHz]
Bandwith W_{b}	125 [kHz]
SF	10
Noise power spectrum density N_0	-174 [dBm/Hz]
Pathloss coefficient a	4.0
Propagation offset b	9.5
Frequency loss component c	4.5
Basic data B_{L}	72 [bit]
Quantization bit size Z	$7, 8, 16$ [bit]
SNR thresholds Γ_{SNR}	-15.0 [dBm]
SIR thresholds Γ_{SIR}	6.0 [dBm]
Packet generation interval G_{p}	10 [min]
Event propagation coefficient α	0.01
Event propagation speed V	1000 [m/s]
x_{min}	-50
x_{max}	50

TABLE II
LEARNING PARAMETERS

Number of epochs T	1500
Q-learning rate η	0.3
Discount rate β	0.95
Set of state $\mathcal{W}$	$\{128, 256, 512, 1024, 2048, 4096\}$

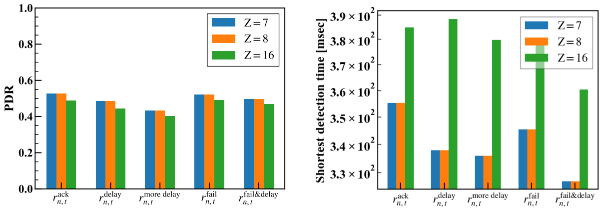
B. Impact of Reward Design

Fig.3 shows the impacts of the reward functions on the performances. The quantization bit size is set to $Z = 8$. Fig.3(a) shows the reward functions considering transmission delay time degrade the average PDR performance. This is because the devices tend to choose smaller DW size. On the other hand, the reward functions that consider the number of transmission failures provide higher PDR performance. Fig.3(b) shows average shortest detection time t_{m}. In Fig.3(b), shortest detection time t_{m} can be reduced by considering the transmission delay time. Thus, we can say that there is a trade-off between the average PDR and the shortest detection time. Since it shows a good trade-off, the reward function given by (20) will be used in the following evaluations.

C. Comparison of Each Scheme

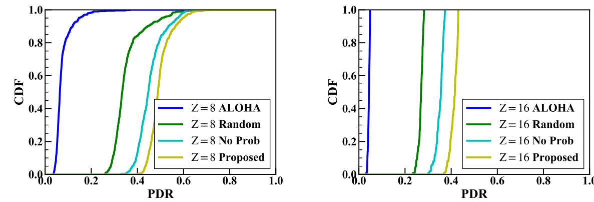
For performance comparison, this paper considers three schemes. The first scheme is a pure ALOHA scheme that is being implemented in LoRaWAN. The second scheme is the random DW allocation scheme with event packet transmission probability. The last scheme is the adaptive DW allocation scheme without event packet transmission probability (hereafter, this scheme is called No Prob scheme).

1) PDR & MSE: Fig.4 shows the average PDR and the mean squared error (MSE) performance of each scheme. In Fig.4(a), the average PDR performance becomes the same for $Z = 7$ and $Z = 8$ due to the same symbol length. The



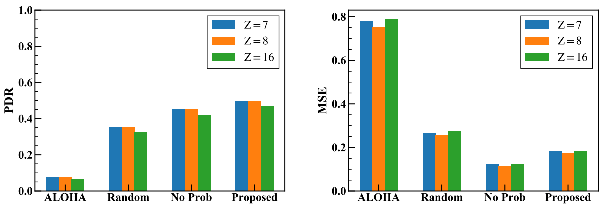
(a) PDR (b) Shortest Detection Time t_{m}

Fig. 3. Impact of Reward Design



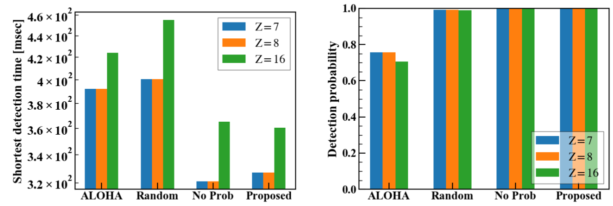
(a) $Z = 8$ (b) $Z = 16$

Fig. 5. PDR of Each Method



(a) PDR (b) MSE

Fig. 4. Characteristics of Each Method



(a) Shortest Detection Time t_{m} (b) Event detection probability at FC

Fig. 6. Other performance of each method

proposed scheme can increase average PDR performance by about 42% compared to ALOHA scheme when $Z = 7, 8$. This improvement is because the proposed scheme can reduce the packet collision probability by the adaptive allocation of DW size and the event packet transmission probability. Fig.5 shows the cumulative distribution function (CDF) of the average PDR with $Z = 8, 16$. From Fig.4(a) and Fig.5, the proposed scheme provides the best average PDR performance. Therefore, the average PDR can be improved by the adaptive allocation of DW size by Q-learning and the control of the number of packet transmission. The MSE performance is affected by quantization bit size Z and the number of successful receive packets. This is because when the number of quantization bit size is small, the packet collision probability decreases but the quantization error increases.

In Fig.4(b), when $Z = 8$, the MSE performance is better than $Z = 7, 16$ at any scheme. This is due to the fact that the effect of PDR performance is greater than the effect of quantization error. The proposed scheme can reduce MSE performance by about 76% compared to ALOHA scheme.

2) Shortest Detection Time & Event Detection Probability: Fig.6(a) shows the shortest detection time at FC. The proposed scheme provides the best performance and can reduce shortest detection time by about 16% compared to ALOHA scheme. Fig.6(b) shows that the proposed scheme can to achieve the event detection probability at FC over 99%.

V. Conclusion

In this paper, an autonomous decentralized transmission timing control was proposed to avoid packet collision. The proposed scheme adaptively controls a DW size to reduce and the number of wireless devices to reduce the packet collision. A Q-learning agent controls a DW size based on the ACK and the number of transmission failures evaluation. Then, the event packet transmission probability is controlled by the transmission delay time that is determined based on the current DW size. The numerical results showed that the proposed scheme could improve the PDR by about 42% compared to the ALOHA scheme.

VI. Acknowledgement

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