Scheduling Algorithm Considering Interference Interval for LPWA

Yudai Yamazaki* and Takeo Fujii*

* Advanced Wireless and Communication Research Center (AWCC), The University of Electro-Communications 1–5–1 Chofugaoka, Chofu, Tokyo 182–8585, Japan

Email: {yamazaki, fujii}@awcc.uec.ac.jp

Abstract-LoRaWAN is one of the radio communication standards of low power wide area network (LPWA) using the chirp spread spectrum. In uplink communication of LoRaWAN, packet retransmission is used to compensate for packet loss due to packet collisions caused by interference coming from other systems on the same frequency band. However, simple packet re-transmission increases packet collisions on the massive system condition since collision avoidance is not considered in LoRaWAN. Therefore, in this paper, we propose an adaptive transmission timing control algorithm for avoiding periodic interference from other systems by estimating their intervals. In our method, an environment with multiple LoRa gateways and LoRa nodes are considered and the received power of interference signals at each LoRa gateway is shared among all LoRa gateways. LoRa gateways can distinguish the system of interfering signals by comparing with the Euclid distances between the data sets of the received power of the interfering signals and the data sets of the received power of the signals come from other interfering systems. In addition, whether the interfering system communicates periodically or not is figured out from the information of the interference interval. LoRa gateways predict the timings that the LoRaWAN system is less interfered considering the periodically interfering systems and control the packet transmission timing of LoRa nodes. The simulation results show the proposed method reduces the packet loss rate compared to the existing system without a significant decrease in throughput.

Index Terms-LPWA, LoRaWAN, spectrum sharing

I. INTRODUCTION

In recent years, the number of IoT devices has continued to increase. According to the literature [1], it is expected that approximately 50 billion terminals will be connected to the Internet by 2020. IoT applications are characterized by low data rates, power consumption, and costs. Therefore, LPWA is focused on a solution to meet these requirements [2].

LPWA is a general category for technologies that provide low-power communications over a wide area, and it enables long-distance communications by using narrow-band communication technologies, spread spectrum technologies and other technologies. In addition, LPWA simplifies the network topology and communication protocol to reduce the device cost and power consumption [3]. In this paper, we focus on an open standard LPWA, LoRaWAN.

The existing LoRa system cannot avoid interference, and each LoRa node can ensure the delivery of messages by retransmitting against packet collisions [4]. However, increased network traffic increases packet collisions and degrades the communication quality. In order to avoid packet collision, it is necessary to recognize the radio environment and to control transmission timings of LoRa nodes appropriately. Adaptive transmission timing control in LoRaWAN systems has been the subject of much discussion because it reduces packet collisions in LoRa systems and improves energy efficiency.

There are scheduling methods for LoRaWAN systems that schedule transmission timing of LoRa nodes with an appropriate Spreading Factor and channel according to the radio environment [5][6]. However, interferences from other interfering systems are not considered in these scheduling methods. It is necessary to recognize the interfering nodes separately in order to avoid the interference based on the past interference information.

There is a method to identify the interfering nodes from a set of interference power obtained by sensing at multiple locations. In [7], a method for estimating the location of a transmitter based on the RSSI at multiple locations is proposed. We use this idea to distinguish interfering signals. In this paper, the clusterized received interference power are considered as multidimensional coordinates and hierarchical clustering with Euclidean distance is applied. Thus, we construct interference signal clusters classified by the similarity of the received power of the interference signals. In addition, the interference interval of each interference signal cluster is calculated by using the interference time of each interference signal in the interference interval is expected to improve the communication quality of the LoRa system.

Therefore, in this paper, we propose an algorithm to control the uplink communication timings of LoRa nodes at a time when packets are unlikely to collide with interference. In the proposed method, multiple gateways recognize the interference signals from the interfering nodes and cluster the interference nodes based on their interference power pairs. Then, the interference interval distribution is calculated for each interference signal cluster. Based on the interference interval distribution, the uplink communication of LoRa nodes is scheduled to a timing that has a lower probability of interference arrival.

The proposed method is evaluated by average packet loss rate and average throughput in a computer simulation. The results show that the proposed method improves the packet loss rate and does not significantly reduce the throughput even when the communication timing is changed.

The rest of the paper is organized as follows. Section II

explains the LPWA. In Section III, we describe hierarchical clustering. Section IV shows the system model, and Section V describes the proposed scheduling algorithm. Simulation conditions are given in Section VI, and Section VII shows simulation results. Finally, Section VIII concludes this work.

II. LPWA

LPWA (Low Power Wide Area) is the general term for power-saving wide-area communication technology. LPWA provides wide-area connectivity for low-power, low-data-rate devices that are not provided by traditional wireless communication technologies [3]. Many LPWA systems use various technologies to achieve long-distance communication, such as spread spectrum and ultra-narrow band technologies. In addition, many LPWA systems use a simple network topology to save power. LoRaWAN uses a star topology where the node and the gateway communicate directly with each other to reduce power consumption. Also, the communication protocol is also simplified, which helps to reduce device costs. These features make LPWA very attractive for use in various sectors such as transportation, healthcare, agriculture, and industry [2]. LoRaWAN is an LPWA that communicates in the Sub-GHz band using LoRa, a physical layer technology for longrange, low-power wireless communication systems [2]. In LoRaWAN, chirp spread spectrum (CSS) is used to improve interference resistance and enable wide area communication. In addition, the communicable distance and data rate in LoRaWAN varies with the spreading rate. The spreading rate is called Spreading Factor and can be selected from 6 integer values between 7 and 12. A higher spreading factor extends the transmission distance while decreasing the data rate. LoRaWAN uses the pure ALOHA-based communication protocol for uplink communication [4]. In pure ALOHA, each node performs uplink communication at an arbitrary time and recognizes packet collision by an ACK packet from the gateway. Since interference avoidance is not performed in pure ALOHA, the probability of receiving a message is increased by retransmitting packets. However, simple packet retransmission increases packet collision in an environment with many interfering nodes.

III. HIERARCHICAL CLUSTERING

Hierarchical clustering is a top-down or bottom-up clustering method that builds a hierarchy of clusters and continues merging or splitting clusters until a stopping criterion is met [8]. Fig. 1 shows an example and a dendrogram of hierarchical clustering. In Fig. 1b, it shows that the clusters are merged according to the distance between clusters. In this paper, we use the average linkage to design the stopping criteria according to the variation of the interference power.

A. Average linkage

Average linkage is a bottom-up hierarchical clustering method. In the average linkage, a distance between clusters is defined as the average of the distances between the elements in each cluster. Therefore, when the distance between two



(a) An example of clustering.



(b) A clustering dendrogram.

Fig. 1: Hierarchical clustering.

elements p,q is denoted by d(p,q), the distance between clusters X and Y is shown by the following formula,

$$\frac{1}{|X||Y|} \sum_{p \in X}^{|X|} \sum_{q \in Y}^{|Y|} \{d(p,q)\}.$$
(1)

Here, we explain how to clustering using average linkage. First, all elements are considered as independent clusters. Next, the pairs of clusters with the minimum distance between clusters are merged in order. This operation is continued until the stopping criterion is satisfied, and then the hierarchy of clusters is constructed. The clustering is stopped in the desired hierarchy by stopping criteria such as the number of clusters and the distance between clusters.

In this article, we cluster the interfering signals based on the power pairs of the interfering signals observed at multiple LoRa gateways. Here, we calculate the interference interval distribution for each interfering signal cluster by using the interference time of the interfering signals included in each interfering signal cluster. Therefore, the interference timing is estimated from the interference interval distribution of the interference signal clusters.



Fig. 2: System model.

IV. SYSTEM MODEL

Fig. 2 shows the system model assumed in this paper. In this work, we assume that there are G(>3) LoRa gateways. L LoRa nodes, and Q interfering nodes. In addition, we consider a situation where the uplink transmission of each LoRa node is scheduled with fixed intervals. As shown in Fig. 2, all the uplink transmissions of the LoRa nodes are scheduled so that they do not collide with each other. In the first step of the proposed method, received power pairs and the interference times from the interference signals observed at multiple LoRa gateways are stored in the database. Next, interference signal clusters are constructed by clustering the stored power pairs. Thereafter, the distributions of the interference interval are created from the interference time for each interfering signal cluster. Here, the previous interference time and the interference interval distribution for each interference signal cluster are used to estimate the timing with high interference probability. Finally, the LoRa nodes scheduled for the transmission timing with high interference probability are scheduled for the timing with low interference probability. Scheduling information is sent to the LoRa nodes via periodic downlink transmissions.

V. ADAPTIVE TRANSMISSION TIMING CONTROL CONSIDERING INTERFERENCE INTERVAL

In this paper, we control the communication time of LoRa nodes based on the estimated interference time. The scheduling procedure is described below.

A. Creating interference signal clusters by sensing at multiple gateway

First, the received power pairs P_{O_j} (p_1, p_2, \ldots, p_G) of the *j*-th interfering signal O_j are determined using *G* gateways and stored in the database with the interference time t_{O_j} . Then, average linkage is applied to the Euclidean distance of each power pair P_{O_1}, \ldots, P_{O_J} for all interference signals O_1, \ldots, O_J . Fig. 3 shows an example of clustering in the case of G = 3. In this example, the stored interfering signals are classified into three interfering signal clusters by their power pairs.



Fig. 3: An example of interfering cluster.

Algorithm 1 Calculate $D_m[x]$	
all elements of $D_m[x]$ are initialized to 0	
for $r = 0$ to $k - 1$ do	
for $f = 0$ to $\left\lceil \frac{\tau_o}{S} \right\rceil$ do	
$D_A[\lfloor \frac{I_r}{S} + f \rfloor] \Leftarrow D_A[\lfloor \frac{I_r}{S} + f \rfloor] + 1$	
end for	
end for	

B. Construction of interference interval distribution

Next, interference interval distribution are calculated in each interfering signal cluster. Based on the interference time t_{O_0}, \ldots, t_{O_k} of the interfering signals O_0, \ldots, O_k in the interfering signal cluster m, the interfering intervals I_0, \ldots, I_{k-1} are calculated. Here, the resolution of interference interval distribution and the packet length of the interference signal are defined as S and τ_o . Therefore, the interference interval distribution $D_m[x]$ of the interference signal cluster m is constructed by the Algorithm 1. The interference interval distribution $D_m[x]$ represents how many packets are observed at the interference interval x/S in the interfering signal cluster m. In the same way, the interference interval distribution $D_1[x], \ldots, D_N[x]$ of all interfering signal clusters N are constructed. Fig. 4 shows examples of the interference interval distributions $D_A[x], D_B[x]$, and $D_C[x]$ calculated for each interfering signal cluster A, B, and C in Fig. 3.

C. Clustering correction using interference interval distribution

In V-A, depending on the location of the interfering nodes and the fading situation, interference signals from different interfering nodes seem to be mixed in the same interference signal cluster. In particular, when interference signals from many interfering nodes are classified in the same cluster, the variation of the interference interval distribution of the cluster increases. Therefore, it is difficult to avoid periodic interference. Hence, we correct the clustering by using the variation of the interference interval distribution $D_1[x], \ldots, D_N[x]$ for each interference signal cluster calculated in V-B. The variance of the autocorrelation coefficients (C_1, \ldots, C_N) corresponding to each interference interval distribution $D_1[x], \ldots, D_N[x]$ are calculated as an indicator of the variation of them. When the



Fig. 4: An example of interference interval distribution.

variation in the interference interval distribution is large, its autocorrelation coefficients are not uncorrelated in time and have positive or negative values for each lag. On the other hand, when the interference interval distribution converges, its autocorrelation coefficient approaches zero for all lags. Thus, we can evaluate the variation of the interference interval distribution by the variance of its autocorrelation coefficient. Therefore, in this step, we focus on interfering signal clusters whose variance of autocorrelation coefficients exceeds the threshold β , and we split the clusters into two temporal clusters from the power pair using the k-means clustering. Then, the variance of the autocorrelation coefficient is calculated from the interference interval distribution of each temporary cluster. If there is a temporary cluster whose variance of the autocorrelation coefficient is below the threshold β , we consider that the distribution of the interference interval is converged by the separation. In this case, we actually divide the interfering signal cluster into two. The above process is repeated for all clusters until it is unable to divide the clusters. This step improves the accuracy of cluster separation.

D. Exclusion of interfering signal clusters with non-periodic transmission

In this method, it is necessary to exclude the interfering nodes that transmit non-periodically because it is impossible to avoid the interference from them. Therefore, we use the autocorrelation coefficients of the interference interval distribution for each interfering node cluster in the same way as V-C. Here, the interfering signal clusters whose variance of the autocorrelation coefficient of the interference interval distribution is higher than the threshold β are considered to be non-periodically interfering signal clusters. In the example of Fig. 4, the interference interval distribution of the interference signal cluster A shows large variations. Hence, cluster A is not considered in the proposed method.

E. Scheduling for LoRa nodes using interference intervals

Finally, we control the transmission timing of all LoRa nodes at every downlink interval T_d . In this work, as described

Algorithm 2 Calculate $E[x]$	
all elements of $E[x]$ are initialized to zero	
for $w = 1$ to W do	
for $x = 0$ to X do	
$E[x] \Leftarrow D_w[\lfloor \frac{c-\iota_{w_f}}{S} + x \rfloor] + 1$	
end for	
end for	

in the system model, we assume that LoRa nodes transmit at regular intervals according to Duty Cycle. Here, the last interference time of the interfering signal cluster w is defined as t_{w_f} . Furthermore, the value of the interference interval distribution corresponding to recent time c is calculated as $D_w[\lfloor \frac{c-t_{w_f}}{S} \rfloor]$. If $D_w[\lfloor \frac{c-t_{w_f}}{S} \rfloor]$ is non-zero, the arrival of an interfering signal from the interfering signal cluster w is estimated at current time c. Therefore, the estimated interference interval distribution E[x] is calculated by combining the interference interval distributions of the periodically interfering signal cluster in the Algorithm 2. Fig. 4 shows an example of the estimated interference interval distribution E[x]constructed from the interference signal clusters B and C.

The packet length and the scheduled next transmission time in the LoRa node are defined as τ_{LoRa} and t_l . If $E[\frac{t}{S}] = 0$ does not always hold for the packet transmission time $(t_l \leq t \leq t_l + \tau_{LoRa})$, then the transmitted packet are estimated to be affected by interference. In this case, we increase t_l until $E[\frac{t}{S}] = 0$ holds for all packet transmission times $(t_l \leq t \leq t_l + \tau_{LoRa})$ without conflicting with transmissions from other LoRa nodes. The above scheduling operation is performed on all LoRa nodes in ascending order of t_l . Finally, the new transmission.

VI. SIMULATION CONDITION

In order to evaluate the usefulness of the proposed method, the average packet loss rate and the average throughput were evaluated by simulation. In this paper, we assume an environment where each LoRa node transmits at intervals of Duty Cycle γ , and the transmission timing of each node is scheduled by the proposed algorithm. LoRa nodes and interfering nodes are assumed to be randomly placed according to uniform random numbers, and gateways are assumed to be located at three fixed locations. In this simulation, each gateway shares information with the database and notifies all LoRa nodes of the scheduling information at every interval of downlink transmission T_d . The interfering nodes that interfere regularly have different transmission intervals to indicate the effectiveness of the proposed method. Thus, transmission interval of *i*-th periodic interfering node is defined as $\frac{\tau_o}{\delta} + i \times \tau_o$. In addition, the communication of the interfering node that communicates non-periodically is based on Poisson process, keeping the Duty Cycle δ . We do not consider the capture effect here. In this simulation, positions of each LoRa and interfering node are changed for each simulation iteration R, and interfering signal

Area size	$2 \times 2 [\mathrm{km}^2]$
Frequency	923 [MHz]
Band width BW	125 [kHz]
Spreading factor SF	10
Coding rate CR	4/5
Number of LoRa nodes L	40
Transmission power of LoRa node	13 [dBm]
Duty cycle of LoRa γ	0.01
Packet length of LoRa τ_{LoRa}	400 [msec]
Number of LoRa gateways G	3
Location of LoRa gateways	(0.5, 1.5) $(1.0, 0.5)$
	(1.5, 1.5) [(km,km)]
Indication interval of downlink	10.000 [mesec]
transmission T_d	10,000 [mesec]
Number of interfering nodes Q	5~30
Ratio of non-periodic interfering nodes σ	0.3
Transmission power of interfering nodes	13 [dBm]
Packet length of Interfering nodes τ_o	400 [msec]
Duty cycle of Interfering nodes δ	0.01
Radio propagation model	Okumura-Hata model(Urban)
Fading model	Rician(<i>K</i> -factor=5), Rayleigh
Max distance between clusters α	14
Threshold of autocorrelation coefficient β	0.002
Resolution of the	100 [msac]
interference interval distribution S	100 [Ilisee]
Maximum interference interval X	2000
Simulation time T	1,000,000 [msec]
Number of simulations R	200

TABLE I: Simulation parameter

clusters are created for every iteration. Moreover, assuming that the dynamic range of the interfering signal power is v[dB], the maximum distance between clusters $\alpha = \sqrt{Gv^2}$ is calculated. In a real environment, the interference signal is observed for a certain period of time and v is obtained by taking the average of the dynamic range of the interfering signal power. In this simulation, we assume that the value of v is 8[dB] and use $\alpha = \sqrt{Gv^2} = 14$. Furthermore, we assumed the Rayleigh fading and Rician fading (K = 5) environment using the Jakes model [9] with reference to the literature [10].

As a comparative method, we consider the existing environment without proposed methods and the four proposed methods with and without clustering correction in V-C and with and without non-periodic interference node exclusion in V-D. The throughput R_b in the performance evaluation is calculated by the following equation,

$$R_b = SF \times \frac{BW}{2^{SF}} \times CR \tag{2}$$

where SF is a spreading factor, CR is a coding rate and BW is a communication bandwidth [11].

Other parameters for the simulation are shown in Table I.

VII. SIMULATION RESULTS

A. Performance under Rician fading (K=5)

Fig. 5 and Fig. 6 show the average packet loss rate and average throughput for the number of interfering nodes in the Rician fading situation. Fig. 5 indicates that all proposed methods improve the packet loss rate compared to the existing environment. In addition, the proposed method



Fig. 5: Average packet loss rate in Rician fading (K = 5).



Fig. 6: Average throughput in Rician fading (K = 5).

with clustering correction shows better packet loss rate than that without clustering correction. The reason for this can be attributed to the interference avoidance by using highly accurate clustering with clustering correction. In addition, Fig. 6 shows that the throughput is improved when the no-periodic interference is excluded, while the throughput is lower than the existing environment when it is not excluded. This performance degradation occurs due to frequent postponement of the transmission timing considering the interference interval of all interfering signal clusters including non-periodic interference signal clusters. Therefore, the proposed method with clustering correction and non-periodic interference exclusion has the best performance in terms of both packet loss rate and throughput.



Fig. 7: Average packet loss rate in Rayleigh fading.

B. Performance under Rayleigh fading

Similar to the Rician fading environment, Figs. 7 and 8 show the average packet loss rate and average throughput for the number of interfering nodes, respectively. Fig. 7 suggests that all the proposed methods improve the packet loss rate in comparison to the existing environment. However, the degree of improvement of the packet loss rate is smaller than that of the Rician fading environment. This is because the clustering accuracy is deteriorated by fading, which causes variation in the interference interval distribution and worsens the accuracy of interference avoidance. Fig. 8 shows that the throughput of the proposed method without clustering correction is lower than that of the existing environment as in the Rician fading environment. The throughput of the proposed method with clustering correction and removal of non-periodic interference is slightly lower than that of the existing environment. The reason for this is that the number of nodes with a postponement of communication time is increased because of the interference avoidance for more clusters wrongly separated by the clustering correction in Rayleigh fading environment. Nevertheless, it can be concluded that the proposed method with clustering correction and exclusion of non-periodic interference has the best performance because it can reduce the packet loss rate and achieve the same level of throughput as the existing environment under the Rayleigh fading environment.

VIII. CONCLUSION

In this paper, we proposed an algorithm to avoid interference from interfering nodes that regularly transmit in LPWA. The proposed method recognizes the interference power from interfering systems at multiple gateways and constructs an interference interval distribution for each interfering system. By using the interference interval distribution, we estimate the next interference timing from the interfering systems and control the transmission timing of LoRa nodes. The simulation



Fig. 8: Average throughput in Rayleigh fading.

results show that the proposed method reduces the packet loss and improves the transmission efficiency.

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