Improving Fault Tolerance of LoRaWAN With Predicting Packet Collision

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***Abstract*— the dependability of IIoT functionality is strongly influenced by its communication protocols. One of the most popular communication standards for the Internet of Things, whose features make it attractive in the IIoT field, is LoRaWAN. LoRaWAN can be considered a low-consumption competitor to cellular networks. This protocol has important features such as long-range coverage, low energy consumption, and a low implementation cost. Although the LoRaWAN features make it a good choice for IoT applications, the existence of real-time constraints and a harsh environment in the IIoT field make it a challenge for network designers to guarantee the dependability of IIoT networks with LoRaWAN. Therefore, in this paper, to overcome this challenge, a novel method is presented for improving energy consumption efficiency, latency, and fault tolerance of the LoRaWAN protocol. The evaluation results show that the proposed method improves packet delivery and latency rate by 11% and 21% compared to standard LoRaWAN.**

Keywords—LoRa, LoRaWAN, Energy Consumption, Latency, Fault Tolerance

I. Introduction

The Internet of Things (IoT) has recently become widely utilized in contemporary society [1]. IoT is composed of sizable computer nodes that link things together online [2]. A significant part of this utilization is to transfer small data such as measuring temperature, pressure, weight, soil PH, and oxygen for different applications such as agriculture, telemedicine, and smart cities [3]. One of the popular IoT communication standards is Low-Power Wide Area Networks (LPWAN), which can be considered as low-power competitors of cellular networks. LPWANs offer crucial characteristics, including extensive coverage, low energy usage, and low implementation cost [4]. One of the popular LPWAN technologies is LoRaWAN, which uses less energy and is less expensive than all other LPWAN technologies [5].

Long Range (LoRa) is the LoRaWAN physical layer registered by Semtech. Lora uses Chirp Spread Spectrum (CSS) modulation for robustness to transmissions [6]. A LoRa radio is characterized by some transmission parameters such as Spreading Factor (SF), Coding Rate (CR), and Bandwidth (BW) [4]. Long-range wide Area Network (LoRaWAN) is a MAC layer protocol that is standardized by the LoRa alliance in 2015. The topology of LoRaWAN is a star of stars. To reduce energy consumption on both the end device and network server sides, it employs the Adaptive Data Rate (ADR) approach. For End Devices (EDs), LoRaWAN utilizes three classes (A, B, and C), with the choice between them causing a trade-off between latency and energy usage [7], [8].

Along with the previously mentioned IoT application of LoRaWAN, its utilization in the Industrial Internet of Things (IIoT) attracts much attention. LoRaWAN is very suitable in industrial fields due to its wide spatial range and low data transfer volume. Also, LoRaWAN can have a very acceptable energy consumption compared to other technologies, which is a deterministic factor in the industrial field [6].

Packet loss is one of the fundamental challenges that LoRaWAN adoption in the industrial field encounters. Packet loss in the LoRaWAN networks can occur for different reasons, including a collision that occurs due to the simultaneous utilization of same spreading factor in the same channel by at least two end devices [2]. Other causes of LoRaWAN network collisions include imperfect orthogonality, channel noise, and high data rates. Collision occurrence in the LoRaWAN network negatively affects reliability, retransmissions, energy consumption, and network latency [6]. LoRaWAN uses Frequency Hopping Spread Spectrum (FHSS) to reduce collisions. So when multiple signals simultaneously arrive at the gate, they are correctly decoded due to the use of different channels and chirp rates. Through the use of a different chirp rate due to the orthogonality of the generated signals, packet collisions are avoided in LoRaWAN [3].

Energy consumption as well as packet loss can be considered deterministic factors affecting the availability of LoRaWAN networks. LoRa is intended for EDs with a long battery life and optimal energy consumption [4]. Both energy consumption and packet loss are increasing with the occurrence of collisions in the LoRaWAN networks. The optimal energy consumption of LoaWAN is an interesting topic for researchers [9]. Although LoRaWAN with ADR improves energy efficiency [8], increased network volume causes high collision occurrences and message retransmissions due to the utilization of the same physical

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layer configuration [3]. In LoRaWAN, when a retransmission occurs, the ADR algorithm increases the SF, which increases the Time on Air (ToA). The ToA increment increases the energy consumption of the network. This scenario gets worse when there are a high number of end devices in the network [10].

The rest of this paper is organized as follows: Section II presents the related work; in Section III, the proposed method is introduced; and Section IV shows the evaluation setup and the simulation results. Finally, the last section concludes this paper.

II. Related Work

Although LoRaWAN is one of the most successful LPWAN technologies, its energy consumption, latency and reliability parameters in the industrial fields is an open issue. So far, many methods have been presented to improve these parameters. These methods can be classified into six categories, as shown in table I.

Table I. Comparison of Methods

Interference	*Latency*	*Energy Consumption*	*Interference- Latency*	*Interference- Energy Consumption*	*Latency- Energy Consumption*
[11]	[29]	[9]	[27]	RM-ADR [20]	[25]
[12]	-	[24]	CA-ADR [7]	G-ADR EMA-ADR [21]	[26]
LoRa+ [8]	-	-	[28]	[22]	-
[13]	-	-	-	HADR [10]	-
[14]	-	-	-	[23]	-
LSTMEKF [15]	-	-	-	-	-
[16]	-	-	-	-	-
EXPLoRa-SF EXPLoRa-AT [17]	-	-	-	-	-
I-ASF [18]	-	-	-	-	-
[19]	-	-	-	-	-

A. Collision

In the paper [11], the authors show that collisions between packets with different SFs can cause packet loss. They also show that high SFs employment for large networks does not necessarily improve network link capacity. In [12], they make predictions for the Packet Delivery Rate (PDR) based on the estimation of channel conditions using offline and online conditions according to machine learning algorithms. In [8], researchers introduce a new mechanism called LoRa+. In LoRa+, a transmission occurs before parameter reception from the GW. In this paper, they consider two criteria, Packet Error Rate (PER) and the packet rejection rate (PRR), to evaluate their work with LoRaWAN in different scenarios.

In [13], an ADR resource management method is introduced. This management method takes place on both sides of the network server and the end device and can speed up the convergence time. In [14], the interference between the Gateway (GW) and the Uplink connection is considered. In this paper, the end devices are distributed according to a homogeneous Poisson point process, and the authors show that the total interference for a gateway follows a non-Gaussian distribution. Reference [15] authors attempt to predict collision occurrences by analyzing the influencing factors. They also perform prediction based on the Long Short-Term Memory Extended Kalman Filter (LSTMEKF) deep learning algorithm.

In [16], a network model that can reduce collisions in small and large-scale networks is presented. In this modeling, according to the Particle Swarm Optimization (PSO) algorithm, SF is first selected, and then it starts sending particles according to the aloha-based method. In [17], they introduce two algorithms, EXPLoRa-SF and EXPLoRa-AT, whose performance in assigning SF to end devices is better than ADR. In the EXPLoRa-SF algorithm, in addition to considering distance measurements, which are the same as Received Signal Strength Indication (RSSI) in the ADR scheme, this algorithm also considers SF based on the total number of connected end devices. The EXPLoRa-AT algorithm, which is more complicated than the first algorithm, tries to equalize the time-on-air of the packets sent in different SFs to reduce collisions.

In paper [18], an Interference-Aware SF (I-ASF) allocation algorithm is proposed. This algorithm takes the gateway sensitivity, interfered SFs, and overlap time of the colliding packets and tries to reduce the time-on-air for the end devices the collision reduction. In paper [19], an analysis of some parameters and configurations of LoRaWAN is performed, which show how the interaction between different adjustable parameters by the system is often difficult to predict, which requires efficient system design and configuration tools. In this article, according to the scenarios they considered, it is possible to find the most suitable configuration according to the existing limitations, including the number of retransmissions, duty cycle, and receiving routes for confirmed traffic.

B. Interference- Energy Consumption

In [20], authors introduce an ADR resource management method for mobile nodes called RM-ADR, which considers packet transmission information (SF and packet forwarding number) and received power, which can improve PDR and energy consumption. In [21], two ADR management methods are proposed on the network server side. One of them is based on a Gaussian filter (G-ADR) for smoothing Signal to Noise Ratio (SNR), and the other one is based on an Exponential Moving Average (EMA-ADR), whose aim is to assign the best SF and TP to mobile and fixed nodes by reducing the convergence period in the confirmed mode, reducing energy consumption, and increasing packet success rate.

In [22], since LoRaWAN ADR suffers unacceptable collisions in large networks, an ADR algorithm that is aware of the SF congestion situation is presented. In this work, the awareness of the congestion in SF makes it possible to improve collision occurrences and energy consumption. In [10], the Hybrid Adaptive Data Rate (HADR) method is employed. HADR is such that it first determines whether the node is static or mobile, and then it can simultaneously select the appropriate resource allocation (SF and TP) for the nodes to send the uplink message. HADR improves the packet success rate and energy consumption compared to ADR (for static nodes) and ADR-Blind (for mobile nodes). Authors of paper [23] performs an analysis of LoRaWAN adaptive data rate performance. This article provides insight into the runtime performance of the ADR algorithm under dynamic link conditions and different network sizes. The results of this paper show that ADR has a high convergence time, and by changing the physical layer parameters, the convergence time, reliability, and energy consumption are improved.

C. *Energy Consumption*

An energy consumption model that takes into account factors such as collision probability and retransmissions is presented in [9]. In this paper, the parameters that affect energy consumption are discussed, such as the node transmission power, the load carried in the data frames, the number of allowed retransmissions, the distance between the sensor and the gateway, and the duty cycle. In [24], the effect of clustering on LoRaWAN transmissions according to the proposed path-based and data-centric algorithms is evaluated. The results of this evaluation showed that clustering can be used to ensure low energy consumption in the network.

D. *Latency- Energy Consumption*

In [25], with gateway redundancy, the backup gateway acts when the main gateway is down so that the end devices can communicate with the network server through the backup gateway. By doing this, they were able to improve the response time and save the energy consumed by the end devices. In [26], data compression is employed to reduce the transmission data volume. A reduction in transmission packet size can reduce the transmission time, and this reduction in transmission time leads to a reduction in energy consumption.

E. *Interference- Latency*

In [27], they performed an analysis to select the most suitable configurations in industrial scenarios that can provide IIoT requirements and answer the key questions about how to configure them correctly. As a result, they were able to improve the probability of collision and delay. The authors of [7] introduce a Collision-Aware ADR called CA-ADR. CA-ADR outperforms conventional methods when connectivity is good, increasing packet success rates and reducing end-to-end latency in the network. In [28], it examines analytical models to investigate the uplink in LoRaWAN in terms of latency, collision, and throughput under duty cycle constraints.

F. *Latency*

The authors of [29] provide a new Time Division Multiple Access (TDMA) protocol that can dynamically allocate time slots to end devices. They also, consider the distance between the end device and the gateway; this helps allocate the best SF to the end device, which can improve data latency.

G. *Comparision of Methods*

In all the previously mentioned methods, only interference, energy consumption, or latency were considered, or only two of the mentioned parameters were analyzed. But none of them could evaluate all these parameters. That's why in this paper a novel method based on channel prediction is proposed to improve interference, energy consumption, and latency in our work.

III. PROPOSED METHOD

In this paper, in order to improve the efficiency of energy consumption, delay and fault tolerance of LoRaWAN, a novel method based on the prediction of the occurrence of collision or interference in the communication channel is presented. In this method, it is assumed that the behavior of the communication channel against each node can be predicted at any time. For the sake of simplicity, the behavior of the communication channel is considered as the success or failure of sending a message with a specific configuration of the physical layer of LoRaWAN at a specific time. As can be seen in Fig. 1, the proposed method has three steps:

- offline modeling;
- Acquisition of transmission permission;
- Sending messages and updating the model.

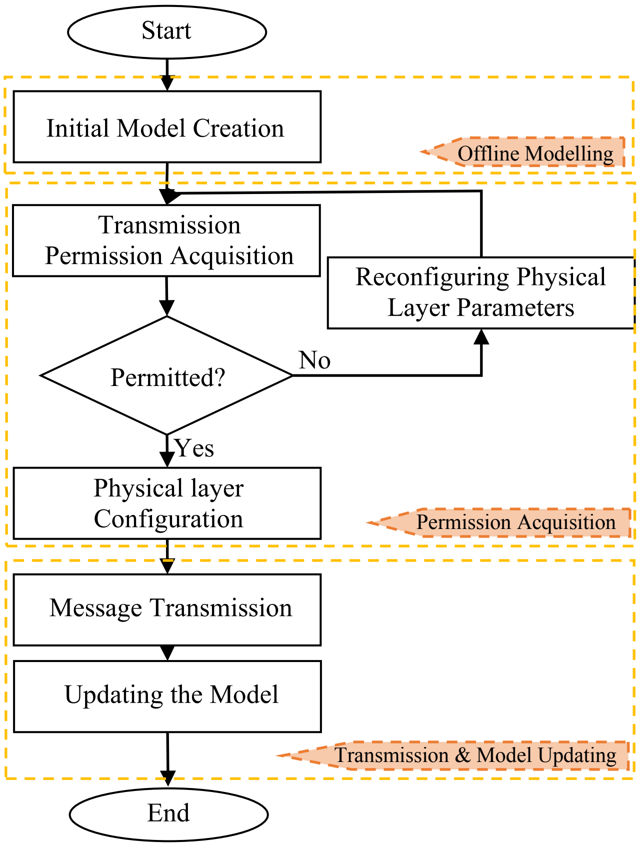

Figure 1. Flowchart of the proposed method

In the initial modeling step, in order to create the channel model, the previously acquired data of the network is employed, in which the success or failure of transmitting messages with different physical configurations (e.g., spread factor, transmission power, and bandwidth) for each node is recorded. In order to create this model, k-means clustering algorithm is utilized. In the Acquisition of Transmission Permission step before sending a message, each node must obtain permission to send for a specific configuration of its physical layer. For this purpose, the configuration parameters are given to the model created using k-means, and if the model predicts the successful sending of the message, the node will be allowed to send its message. Otherwise, if the transmission is predicted to fail with the current physical layer configuration, the physical layer parameters must be changed. The change of these parameters is such that it results in the least increase in delay and energy consumption. For this purpose, first the bandwidth is changed, if it does not succeed in obtaining permission with this change, then the transmission power is changed, and finally the spread factor is changed. The flowchart of physical layer reconfiguration van be seen in Fig. 2.

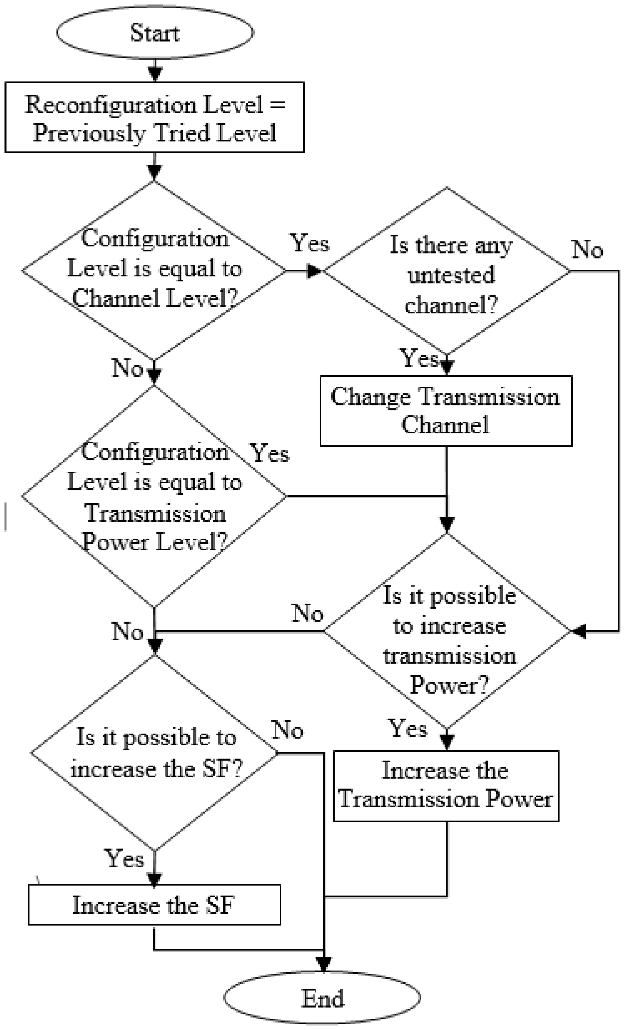

Figure 2. Physical Parameters Reconfiguration

In the final step, each node reconfigures its physical layer with new parameters, sends a message, and finally, whether this message transmission is successful or not, it updates its channel model.

IV. Evaluation

In this section, the proposed method is evaluated through simulation and hardware implementation. In order to show the efficiency of the proposed method, parameters like energy consumption, PDR, and latency are compared with those of standard LoRaWAN.

A. Simulation Results of the Proposed Method

The performance of the proposed method in terms of energy consumption and PDR is evaluated using LoRaSIM. LoRaSIM is a discrete event simulator based on SimPy that can be employed to measure parameters such as the energy consumption and PDR of nodes. The goal is to estimate the channel collision with the previously created dataset and choose the best physical layer configuration for the end devices. LoRaSIM is used to generate the dataset required for training the K-means clustering algorithm of the proposed method. As can be seen in Table II, this dataset contains the successful and unsuccessful transmissions, with a specific physical layer for each node.

Table II. Initial Dataset

Node Index	*SF*	*SC*	*Transmission Power*	*Successful or Unsuccessful*
92	11	868100	14	Successful
23	12	868500	8	Successful
…	…	…	…	…
63	9	868500	14	Unsuccessful

As expected in the deployment of the Internet of Things, we have considered a centralized gateway and 100 static end devices in a 10x10 km area that are randomly placed around the gateway, Fig. 3 shows the location of the gateway and end devices. End devices from SFs 7 to 12 in the European frequency band of 868 MHz with three different channels are considered to send their packets to the gateway. In Table III, we summarize the main simulation parameters.

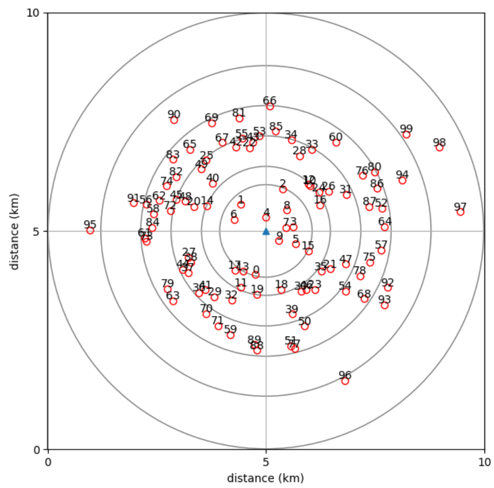

Figure 3. Nodes Arrangement of Simulation

Table II. Simulation Parameters

parameter	*value*
BW (*BW*)	125 kHz
SCs (SC)	{868100, 868300, 868500} Hz
SFs (SF)	{7,8,9,10,11,12}
TP (T P)	{8,11,14} dBm
CRs (CR)	4/5 Hz
Path loss model	*Log - distance*
Duty cycle (*DC*)	1%
Packet length (*L*)	50 bytes
Simulation time (hourse)	30000
Packet transmission interval	15 packets/hour (4*60*1000 ms)
GWs number (*GW*)	1
EDs number (*N*)	100
Field size area	10000 * 10000 m
Class	A
Mode of Communication	Unconfirmed

The PDR result of the simulation is shown in Fig. 5. As can be seen in this figure, the proposed method improves packet delivery rates by an average of 11% compared to standard LoRaWAN.

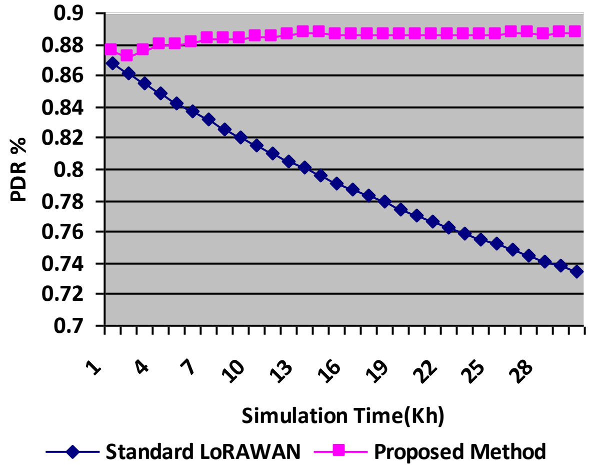

Figure 5. PDR Evaluation Results

The result of the energy consumption evaluation is presented in Fig. 6. According to this figure, the energy consumption of the proposed method has increased by an average of 7% compared to the standard LoRaWAN. Although the evaluation results show that the proposed method has a higher energy consumption than standard LoRaWAN, this evaluation does not cover the effect of message retransmission on energy consumption because in the simulation setup all messages are considered unconfirmed types. Since in industrial fields messages need to be acknowledged and retransmitted after a collision occurs, and as shown in Fig. 5, the PDR of the proposed method converges to 88%. While in the standard LoRaWAN method, the PDR decreases during the simulation, so if all the messages are of the confirmed type, the proposed method also improves the energy consumption.

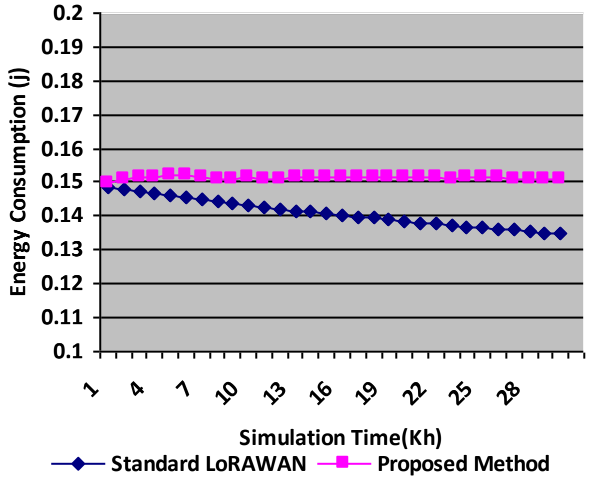

Figure 6. Energy Consumption Evaluation Results

B. Evaluation Results

C. of the proposed method in Test Bed

In addition to the simulation, in order to evaluate the latency improvement of the proposed method, a test bed using the LoRa-Ra01 module is deployed. The implementation of the test bed is shown in Fig. 7. As can be seen in this figure, the AtMega328 and ESP8266 are used as end devices, and the Gateway respectively.

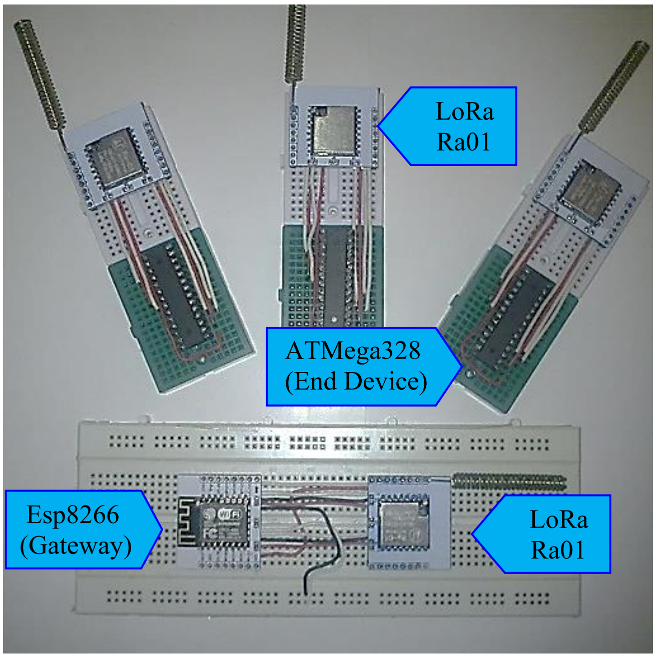

Figure 7. Implementation of Test Bed

To evaluate the latency improvement of the proposed method, each node of the test bed randomly generates a packet at specified time intervals. To increase the likelihood of a collision, the nodes are placed at equal distances from the gateway. The evaluation results are presented in Fig. 8. As can be seen in this figure, by decreasing the time interval, the average latency of standard LoRaWAN is 21% higher than the proposed method.

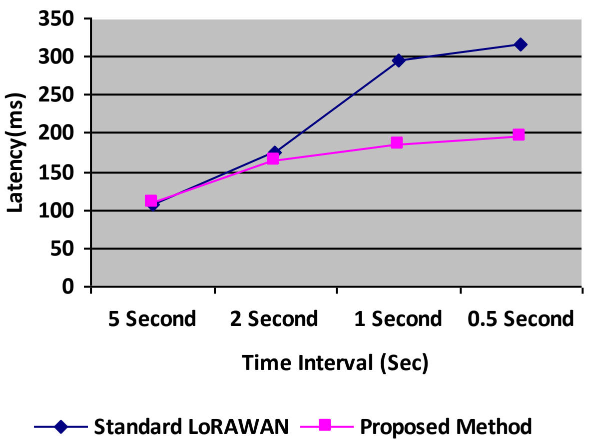

Figure 8. Latency Evaluation Results

V. CONCLUSION

Although LoRaWAN has a low implementation cost and energy consumption, its latency and packet delivery rate go against the real-time and reliability requirements of the IIoT. As a result, in this paper, by predicting collision occurrence, a novel method is presented to avoid packet loss. This decrease in packet loss improves LoRaWAN reliability by increasing packet delivery rate and energy consumption efficiency by avoiding message retransmission. The evaluation results show that the PDR of the proposed method has converged to 88% and that latency compared to standard LoRaWAN is improved by an average of 21%.

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