Adaptive Data Transmission Method According to Wireless State in Long Range Wide Area Networks

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Abstract: The Internet of Things (IoT) has enabled various intelligent services, and IoT service range has been steadily extended through long range wide area communication technologies, which enable very long distance wireless data transmission. End-nodes are connected to a gateway with a single hop. They consume very low-power, using very low data rate to deliver data. Since long transmission time is consequently needed for each data packet transmission in long range wide area networks, data transmission should be efficiently performed. Therefore, this paper proposes a multicast uplink data transmission mechanism particularly for bad network conditions. Transmission delay will be increased if only retransmissions are used under bad network conditions. However, employing multicast techniques in bad network conditions can significantly increase packet delivery rate. Thus, retransmission can be reduced and hence transmission efficiency increased. Therefore, the proposed method adopts multicast uplink after network condition prediction. To predict network conditions, the proposed method uses a deep neural network algorithm. The proposed method performance was verified by comparison with uplink unicast transmission only, confirming significantly improved performance.

Keywords: IoT, wide area communication, machine learning, uplink transmission.

1 Introduction

Recent information and communication technology advances have enabled small devices to collect data and forward it to remote servers, which is ultimately employed to provide intelligent services. This network architecture applies to most Internet of Things (IoT) services, including smart home, smart city, smart factory, smart farm, healthcare monitoring, etc. [Jing, Miao and Chen (2018); Gubbi, Buyya, Marusic et al. (2013); Wang, Gao, Yin et al. (2018); Yin and Wei (2019); Su, Sheng, Leung et al. (2019)]. Emerging long range wide area (i.e., low power wide area: LPWA) communication technology has already enabled long-range IoT services. It can transmit a packet up to 15 Km in single hop transmission and have 50 Kbps as maximum data rate. The receiver sensitivity of the LPWA is about -145 dBm. That is, LPWA communication technology

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Received: 27 December 2019; Accepted: 26 February 2020.

transmits small data packets with very low power, while retaining relatively large transmission distances. Fig. 1 represents a typical LPWA network architecture. The LPWA is composed of numerous end-devices, several gateways, and a network server. Collected data from the end-devices is delivered to a network server, and an application server connects to the network server to exploit network server data to offer relevant services. A network server controls the LPWA network [Xiong, Zheng, Xu et al. (2015); Raza, Kulkarni and Sooriyabandara (2017); Centenaro, Vangelista, Zanella et al. (2016); Kim, Kim, Hassan et al. (2017); Kim and Kim (2019)]. Major traffic flow is uplinked from end-devices and a network server via a gateway.

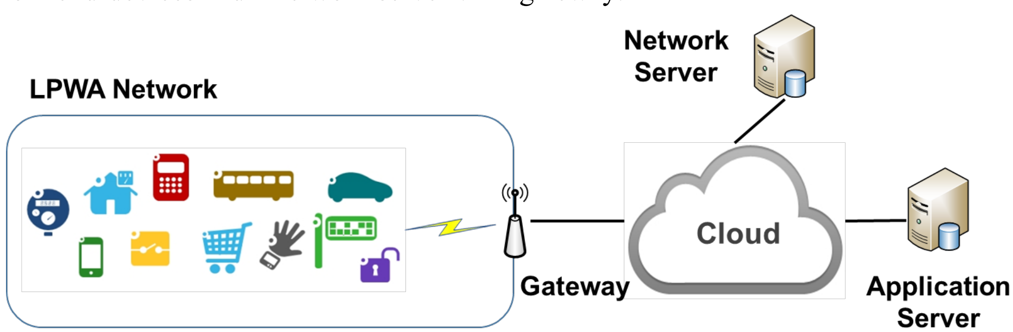

Figure 1: Typical LPWA network

The core consideration for LPWA networks is to ensure robust wireless communication. Thus, data can be transmitted considerable distances. The transmitting to a network server(s) use very low data rate and small data packets for long range transmission, and hence long transmission delays can occur. The potentially long transmission distance means LPWA networks tend to have many end-devices in a single gateway area, which requires even stricter uplink data transmission efficiency. When numerous end-devices attempt to transmit a packet, network congestion can occur and this causes to drop the successful data transmission. In addition, the long range wireless conditions can be frequently changed to bad. LPWA networks comprise resource limited end-devices and cannot control efficient data transmission by exchanging control messages. Additional messages usage increases energy consumption of end-devices and transmission delays.

Under poor wireless conditions, if a packet loss occurs in the LPWA network, conventional technologies attempt to retransmit the lost packet. After several subsequently unsuccessful retransmission attempt, they reduce transmission data rate by changing their modulation scheme. Reduced data rate can improve the number of successful data transmissions when wireless conditions are bad. However, it takes a long time to control the data rate [Sornin, Luis, Eirich et al. (2016); Augustin, Yi, Clausen et al. (2016); LoRa Alliance (2019); Cao, Zheng, Ji et al. (2018); He, Xie, Xie et al. (2019)]. In addition, because the transmission time of a single packet is long in LPWA networks, long packet transmission delays are caused as the retransmission is increased. Thus, a proper transmission method is essential even in poor LPWA network, or other conditions.

This paper proposes a novel end-device transmission method for network conditions. Fundamentally, there are many gateways within end-device communication range. Therefore, the probability of successful data transmission will also probably be increased if end-devices exploit multicast for uplink data transmissions under bad network conditions. This scheme should reduce long transmission delay under bad conditions. This paper considers and investigates various parameter effects for the proposed multicast system. Uplink multicasts form the basis for uplink multicast decisions, multicast group management, and uplink multicast transmission. We evaluated the proposed method performance compared with conventional approaches and showed the resulting predictions match observations reasonably well.

The remainder of this paper is organized as follows. Section 2 discusses LPWA networks as the related work. In Section 3, the proposed method is explained. Performance evaluation and the results are described in Section 4. The paper is concluded in Section 5.

2 Related work

Several communication technologies are employed for LPWA networks, including LoRaWAN, SigFox, LTE-M, NB-IoT, etc., [Catalano, Coupigny, Delclef et al. (2018); SIGFOX (2019); Díaz-Zayas, García-Pérez, Recio-Pérez et al. (2016); 3GPP TR 36.802 (2016)]. The long range wide area network (LoRaWAN) technique best represent communication technology adopted over this unlicensed band [Xiong, Zheng, Xu et al. (2015); Raza, Kulkarni and Sooriyabandara (2017); Centenaro, Vangelista, Zanella et al. (2016)], and is consequently widely used in long range IoT services. LoRaWAN transmits a data packet and waits for an ACK packet during receive_delay. ALOHA as a medium access control scheme is used to transmit packets in shared wireless media of LoRaWAN. Fig. 2 shows the data transmission of LoRaWAN. The packet is retransmitted if the original transmission failure occurs. If there is no response within adr_ack_delay, the end-device selects a lower data rate to maintain connectivity, since the modulation scheme for lower data rate can provide robust wireless transmission [Sornin, Luis, Eirich et al. (2016); Augustin, Yi, Clausen et al. (2016); LoRa Alliance (2019)]. This adaptive data rate (ADR) control is essential for data transmission under poor wireless conditions. However, it takes a long time to reduce the data rate to an appropriate value. If uplink multicast is available in LPWA networks, an end-device can send data to multiple gateway in a single transmission even though wireless conditions are bad. When data arrives at one of the gateways, it can be forwarded to a network server. A network server can stably collect data from the long range IoT domains. Therefore, the proposed method attempts to multicast data to several gateways, to increase the probability of data delivery. However, the conventional LoRaWAN supports only downlink multicast scheme and does not consider uplink multicast scheme. LoRaWAN's downlink multicast serves to propagate the same command from the network server to end-devices in long range IoT domains.

As mentioned earlier, LoRaWAN provides multicast data transmission downlinks, supporting up to four multicast groups, where end-devices identify multicast groups by their multicast ID and address. To reduce protocol overhead, the multicast ID can be used. End-devices organize the multicast group by exchanging several messages. Like a unicast network join procedure, end-devices can join a multicast group using a multicast join procedure as shown in Fig. 3. An end-device sends the *Multicast_Join_Request* message to a network server to be a member of a multicast group. When the network server receives the message, it forms a multicast group and responds to the end-device with the *Multicast_Join_Accept* message. Then, the end-device receiving the message is assigned the multicast group address and can receive multicast data from the network server. LoRaWAN multicast provides commands to end-devices for managing multicast groups. If end-devices are included in a multicast group, a network server can send commands to the multicast group, and hence achieve significantly more efficient multicast transmissions than unicast [Stokking and Yegin (2018); Lim and Lee (2018)].

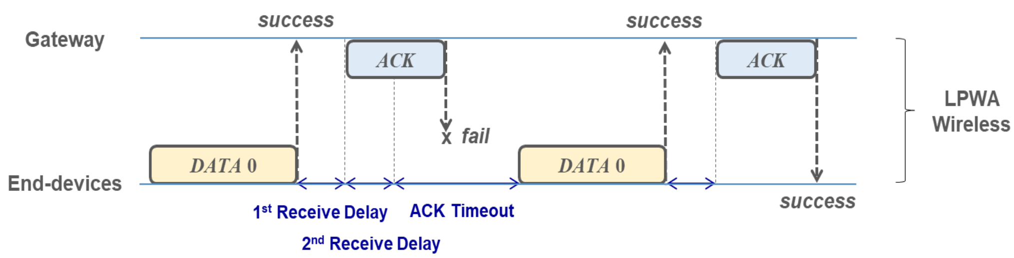

Figure 2: LoRaWAN data transmission

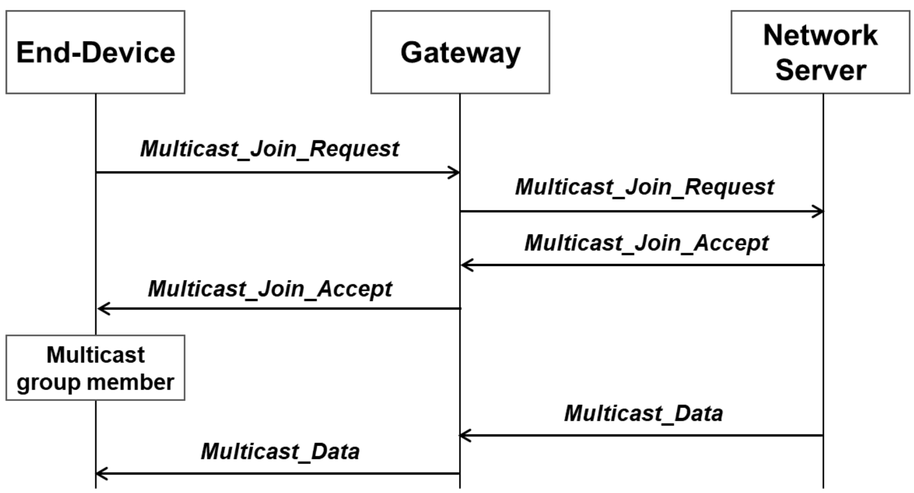

Figure 3: LoRaWAN multicast procedure

However, LoRaWAN's multicast flow is downlink. In LPWA networks, major traffic flow is uplink and LoRaWAN's major traffic flow is also uplink. Thus, multicast uplink in major traffic flow should be considered for efficient data transmission in long range IoT areas. The proposed method exploits uplink multicasting to increase data delivery probability under bad wireless conditions. Therefore, the proposed method includes decision making for uplink multicast, uplink multicast group management and multicast transmission.

3 Proposed approach

Since LPWA networks transmit data packets with very low power and wide communication range, there are generally several gateways within communication range of an end-device.

Therefore, the end-device must select the optimal gateway. As discussed above, the network has very low data rate and hence takes considerable time to transmit a data packet. If network wireless conditions are bad, data transmission will take more time due to retransmissions. Although long range IoT service data in LPWA is not time sensitive, long transmission delays could make it difficult to accurate and timely provide services. Thus, LPWA networks strongly require a method to reduce transmission delays. The proposed method identifies wireless conditions through learning and then performs uplink multicast transmission if the wireless condition is considered to be bad from the learned result.

3.1 Wireless condition prediction

A classifier algorithm for machine learning is used to predict states in various situations. The classifier algorithm learns the wireless state of LPWA networks from relevant network parameters, including signal strength (x_1) and data rate (x_2). Input parameter (X) is described with data attributes (x) and their weights (w).

$$X = w^T x = w_1 x_1 + w_2 x_2 + b = \sum_{i=1}^{n} w_i x_i + b \,, \tag{1}$$

where if w_0 is 1 and x_0 is b, the Absolute (1) becomes as

$$X = \sum_{i=0}^{n} w_i x_i \,, \tag{2}$$

where n is 2 because data attributes are two (i.e., x_1 and x_2).

For the learning, the proposed classifier algorithm employs a deep neural network comprising two input nodes in the input layer and one output node in the output layer with nine hidden layers. The hidden layers include layers of seven and four nodes crossing each other. Fig. 4 shows the proposed deep neural network learning model. In the deep neural network, the output of each node connects to the input of a node in a next layer. Then, the input at the j-th node of a layer l is represented as

$$u_j^{(l)} = \sum_{i=1}^{n} w_{ji}^{(l)} z_i^{(l-1)} + b_j^{(l)} \,, \tag{3}$$

where $z_i^{(l-1)}$ is the output of the i-th node in a previous layer and $w_{ji}^{(l)}$ is a weight for i-th input at the j-th node of a current layer l. $b_j^{(l)}$ means a bias for the j-th node. When $w_{j0}^{(l)}$ is $b_j^{(l)}$ and $z_0^{(l-1)}$ is 1, the Eq. (3) can be

$$u_j^{(l)} = \sum_{i=0}^{n} w_{ji}^{(l)} z_i^{(l-1)} \,. \tag{4}$$

Then, the input parameter X is indicated to $u_j^{(2)}$

The output at each node (z_j) is made by an activation function ($f(\cdot)$).

$$z_j^{(l)} = f(u_j^{(l)}) = f\left(\sum_{i=0}^{n} w_{ji}^{(l)} z_i^{(l-1)} \right). \tag{5}$$

The output of the final layer becomes a hypothesis h for the given inputs X. When the real output is y, there exists errors between y and h. The errors can be represented using an error function. In the proposed method, the mean squared error function is used.

$$E = \frac{1}{2}\|y-h\|^2 = \frac{1}{2}\sum_j (y_j - h_j)^2 \ . \tag{6}$$

The errors can be minimized by learning. Through applying an optimization algorithm to the error function, the optimized weight (w_{ji}) of each node of the neural network can be obtained. Wireless condition prediction is performed with the optimized weights. In the proposed neural network, we use *tanh* as the seven nodes layer activation function, and *ReLU* for the four nodes layer. The output layer activation function is sigmoid. Training data is computed according to the forward direction of the deep neural network, and weights of each node in the neural network are optimized by backpropagation algorithm to minimize errors [Zhang, Patras and Haddadi (2019); Goodfellow, Bengio and Courville (2016)]. The proposed learning model achieves better accuracy with increased training data size.

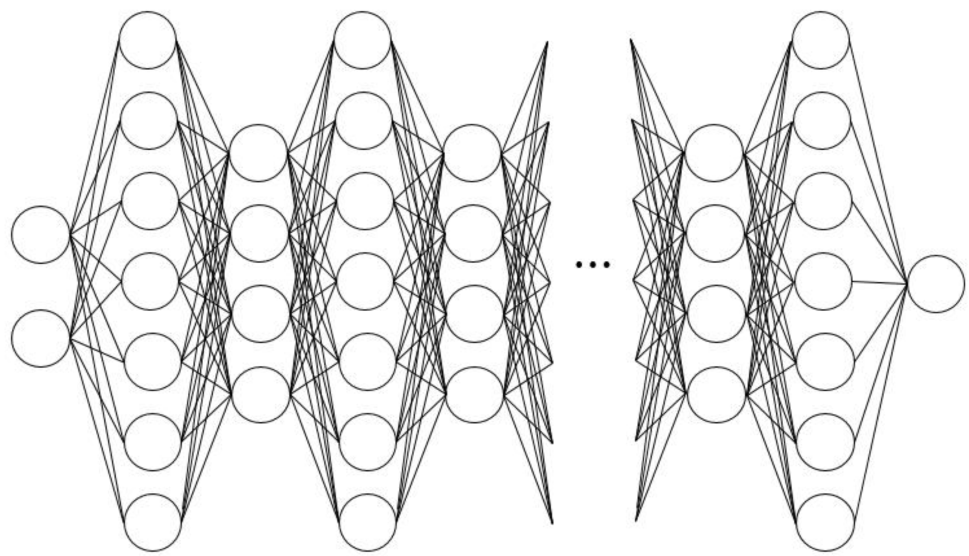

Figure 4: The proposed deep neural network model

The propose deep neural network model can be operated in the LPWA gateway. Because end-devices in the LPWA network do not have enough computing resources, learning with a lot of data in the end-device is not appropriate. Thus, the LPWA gateway performs learning for the network prediction and then shares decision parameters for a classifier to end-devices. Then, the end-devices use the parameters to predict network conditions.

3.2 Uplink multicast group management

Uplink multicast groups are constructed to send multicast data from an end-device to adjacent gateways. The proposed approach performs uplink multicast when wireless conditions are bad, to improve packet forwarding probability. Thus, the uplink multicast does not require an additional procedure to manage the multicast groups. An end-device receives multicast group information through the network join procedure for unicast transmission [Sornin, Luis, Eirich et al. (2016); Augustin, Yi, Clausen et al. (2016); LoRa

Alliance (2019)]. Fig. 5 shows the procedure to obtain uplink multicast address, with detailed process as follows.

· The end-device sends a *join_request* message to a network server via its gateway.

· The gateway piggybacks an adjacent gateway list and relays the message.

· The network server then allows the end-device to join the network, assigns an uplink multicast address to a group of gateways, and sends this information along with the list of the group to the end-devices' gateway.

· The gateway receives the *join_accept* message and group list, sends *join_accept* message to the end-device and forwards the uplink multicast address to the gateways in the group list.

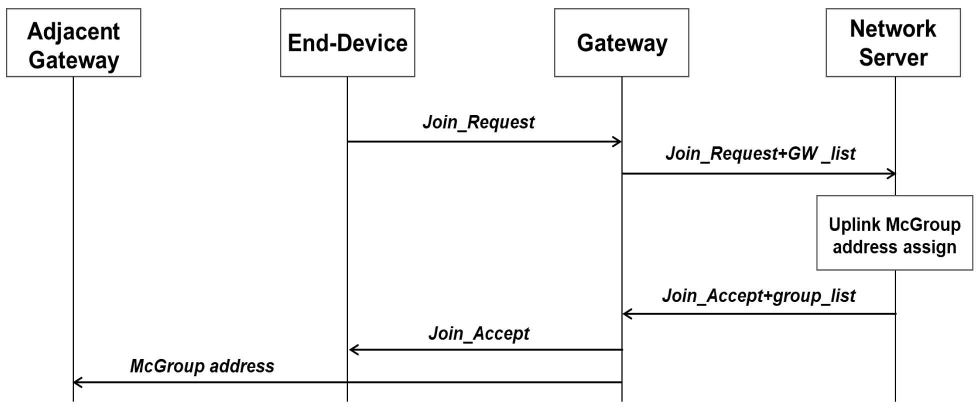

Figure 5: Procedure to obtain uplink multicast address

3.3 Uplink multicast transmission

The proposed approach uses unicast transmission if possible, and multicast transmission if wireless conditions are bad. Data learning to predict LPWA wireless condition is performed in a gateway deriving system parameters for the classifier algorithm and delivering them to end-devices. End-devices subsequently predict wireless conditions using these parameters. Fig. 6 shows that wireless condition prediction is performed periodically. The end-device determines a transmission mode depending on the predicted state: unicast or multicast. The end-device periodically predict wireless conditions using the received information for the deep neural network model. If wireless conditions are predicted to bad, the end-device forward packets using uplink multicast with multicast group address. The end-device uses the multicast group address obtained previously in the network join procedure. If wireless conditions are good, the end-device maintains uplink unicast to forward packets.

A multicast data packet is transmitted to all gateways in the multicast group, but not all gateways may receive the packet depending on wireless conditions. If the multicast packet is delivered to an end-device's gateway, LPWA data is converted to an IP packet and forwarded to a network server. If adjacent gateways receive the multicast packet, they forward the packet to the end-device's gateway. The forwarded packet is converted to the IP packet for the network server in the gateway, and then sent to the network server.

```
Uplink-Multicast (x1, x2, GW, Mcast)
x1: Signal strength
x2: Transmission rate
GW: Gateway address of the end-device
Mcast: Uplink multicast group address
repeat per periodic-interval:
    wireless ← deep-Neural-Network (x1, x2)
end repeat

if wireless is bad :
    dest ← Mcast
    forward (dest)
else
    dest ← GW
    forward (dest)
end if
```

Figure 6: Uplink multicast transmission of the proposed method

In uplink unicast, successfully transmitted packets can be represented as

$$\Theta(N) = \sum_{n=1}^{N} \left(n \times P_{ucast}(N,n) \right), \tag{7}$$

where N is total transmitted packets and $P_{unicst}(N,n)$ is a forward probability for n packets among N packets. The forward probability is calculated as

$$P_{ucast}(N,n) = \binom{N}{n} \times (1-p)^{n} \times p^{N-n}, \tag{8}$$

where p is a wireless error probability.

In uplink multicast, multiple gateways can receive packets from end-devices. Successfully transmitted packets in uplink multicast can be represented as

$$\Theta(N) = \sum_{n=1}^{N} \left(n \times P_{ucast}(N,n) \times M \times p_{a} \right). \tag{9}$$

M is searched gateways in an end-device and p_a is a probability of activated gateways. The activated gateway means a gateway can receive uplink multicast packets from end-devices. In the LPWA network, an end-device transmits a packet with a single hop transmission. When gateways are exponentially distributed with λ, their density function is

$$f(l) = \lambda e^{-\lambda l}, \qquad l \geq 0, \tag{10}$$

where l is a hop distance. Then, p_a can be represented as

$$p_a(l) = \int_0^l \lambda e^{-\lambda l} dl = 1 - e^{-\lambda l} \text{ .} \tag{11}$$

Because l is 1, p_a becomes 1-$e^{-\lambda}$. If $M \times p_a$ is greater than 1, the uplink multicast probability is greater than the unicast probability and can successfully transmitted more packets to a network server.

4 Performance evaluation

4.1 Deep neural network implementation

The proposed approach exploits a deep neural network to predict wireless conditions (Section 3.1), implemented with TensorFlow et al. [TensorFlow (2019); Keras (2019)] APIs. We employed the Adam optimizer, since it considers gradient direction and size, and hence obtains efficient and accurate computation results. We employ LPWA signal strength and data rate to predict wireless conditions. Tensorflow and Keras are open source libraries implementing deep learning models and have been widely used for many applications. We trained the learning model using 7,000 LPWA network data, and subsequently validated with additional 3,000 LPWA network data. Fig. 7 shows learning results of the test data set. The learning accuracy of the proposed deep neural network model is 93.7%, and the existing logistic regression model, which is the representative learning model for a classifier, is 74.3%. The proposed learning model using a deep neural network algorithm shows better accuracy than the existing learning model.

The proposed LPWA transmission method then applies the learning results to unknown samples collected from the LPWA network, as shown in Fig. 7. LPWA network end-devices then predict wireless conditions based on trained classifier parameters.

```
7000 train + 3000 test
10000/10000 [==============================] - 0s 9us/step
10000/10000 [==============================] - 0s 9us/step

 Loss: 0.0522. Accuracy: 0.9333

 Test loss:  0.04975104188422362
 Test accuracy:  0.9369999766349792
```

(a) Proposed deep neural network model

```
7000 train + 3000 test
10000/10000 [==============================] - 0s 7us/step
10000/10000 [==============================] - 0s 7us/step

 Loss: 0.1951. Accuracy: 0.7344

 Test loss:  0.19125307619571685
 Test accuracy:  0.7426666617393494
```

(b) Existing logistic regression model

Figure 7: The result of training and test set

4.2 Uplink multicast transmission

Computer simulations were implemented using the SMPL C library [MacDougall (1987)] for event driven computer simulation. Two states Markov chain [Ross (2002); Trivedi (2002)] were considered for wireless channel model: good and bad as shown in Fig. 8. Good state is changed to bad state with a probability p. Bad state is changed to good state with a probability q. p and q are set to 0.3 and 0.7, respectively. Packet error rate was assumed to be 0.05 and 0.10, respectively. Wireless conditions were changed according to exponential distribution with mean NET_INTERVAL.

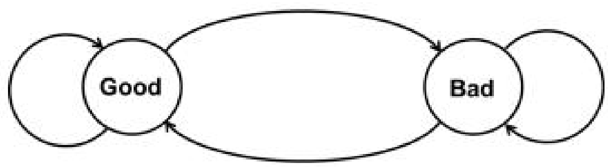

Figure 8: Two state Markov chain for the wireless channel model of the LPWA network

The NET_INTERVAL is set to 5 min. In the wireless channel model, retransmissions due to transmission failure were not considered for the simulation. End-device data traffic was generated with uniform random distribution (mean 10 min), and simulation time was set to 7 days. We assumed the end-device was located within the coverage of three gateways. Tab. 1 represents the simulation environments.

Table 1: Simulation environments

Parameters	Values
Simulation Time	7 days
Network Change Interval	5 min
Traffic Generation Interval	10 min
Wireless Prediction Accuracy	94%
Transmission Slot Time	500 ms
Number of Neighbor Gateways	3

Fig. 9 shows simulation results of the proposed approach. The end-device sent 2,017 data packets over the 7-day period, with 1,947 packets successfully delivered to the network server, and uplink multicast occurred 639 times. Thus, the proposed approach provided 96.5% transmission success. That is, the proposed approach improves the probability of data delivery by using uplink multicast in the bad wireless condition. Thus, the proposed method can obtain more data packets in a network server.

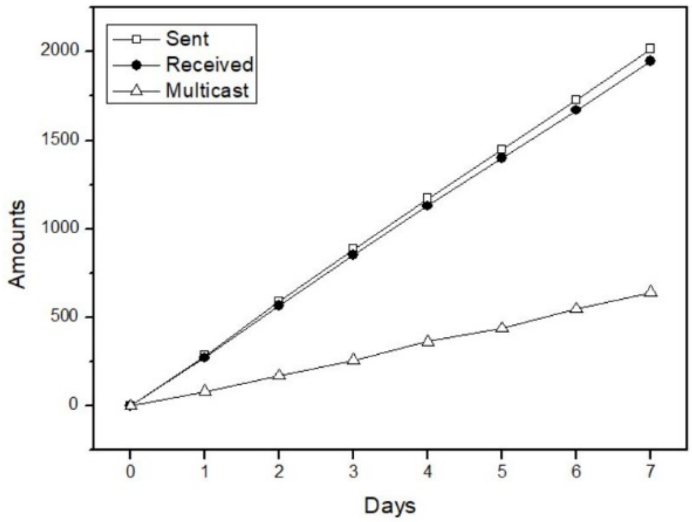

Figure 9: The result of the proposed approach

Fig. 10 compares simulated received data packets at the network server for conventional and proposed approaches. Overall, the conventional approach successfully transmitted 1887 data packets (93.5%), compared with the proposed approach 96.5% success rate, i.e., 3% performance improvement. Including retransmission and energy consumption considerations in the simulation would increase the proposed approach advantage over the conventional approach. In addition, as mentioned earlier, the improvement of the forward probability on wireless leads to the increment of the amount of received data packets. If the wireless prediction accuracy is increased, uplink multicast is used in appropriate situation and the forward probability can be increased. This causes to increase the collected data at a network server.

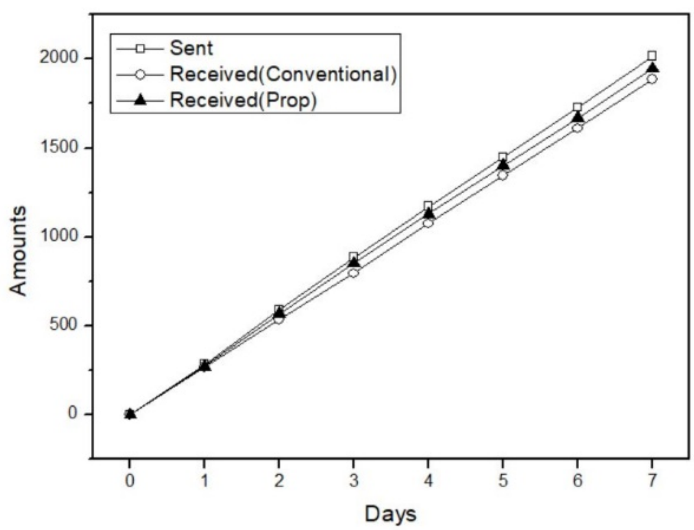

Figure 10: The result of received data packets in the network server

Fig. 11 represents the retransmission counts during the computer simulation. Retransmissions occurred 105 times in the proposed approach. In contrast, the conventional approach is 187 times. Uplink multicast can significantly reduce the number of retransmissions. Retransmission in wireless networks means more communication energy consumption. Thus, the proposed approach has less energy consumption than the conventional approach. It can improve lifetime of the long range IoT systems. That is, the proposed approach reduces energy consumption by improving transmission efficiency through increasing the transmission probability.

Tab. 2 shows accumulated transmission delays. If the LPWA end-device fails to transfer data, computer simulation allows two retries. As retransmissions increase due to transmission failures, the transmission delay also increases. As shown in Fig. 11, the conventional approach has more retransmission counts. Because the LPWA communication has long transmission slot to deliver data packets far away, the retransmission causes long transmission delays. Therefore, the proposed approach can reduce the transmission delay because it reduces the retransmission by uplink multicast. The LPWA communication is a long range IoT system and the end-device has insufficient resources. It has constrains to use additional messages to improve data transmission efficiency. Thus, the proposed approach becomes a considerable way to improve transmission efficiency in LPWA communications.

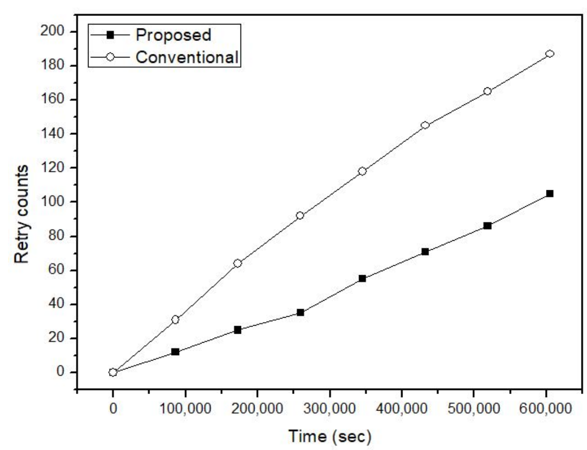

Figure 11: Retry counts during the computer simulations

Table 2: Transmission delays (sec)

Time	Proposed	Conventional
86,400	212	216
172,800	424	445
259,200	631	660
345,600	842	880
432,000	1,061	1,102
518,400	1,268	1,313
604,800	1,476	1,533

5 Conclusions

LPWA networks commonly incorporate numerous end-devices, typically within several gateways' communication ranges. LPWA communication has long transmission delays but has few resources available to generate network control messages due to insufficient computing resources. Therefore, methods are required to improve data transmission efficiency without generating additional control messages, particularly under bad wireless conditions. The proposed approach employs uplink multicast transmission when it identifies bad condition state, thereby improving communication efficiency without requiring network control messages. Decision making is implemented using a deep neural network classifier algorithm. Simulations confirmed significant performance improvement in terms of successfully received data packets at the network server. However, the analysis did not consider retransmission or energy consumption, which would also be significantly improved under the proposed approach. Thus, the proposed approach provides a practical and viable alternative to improve transmission success for LPWA networks without increasing network overhead.

Acknowledgement: This research was supported by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2019-2015-0-00403) supervised by the IITP (Institute for Information & communications Technology Planning & Evaluation), and this work was supported by the Soonchunhyang University Research Fund.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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