Improvement of RSSI-Based LoRaWAN Localization Using Edge-AI

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Abstract. Localization is an essential element of the Internet of Things (IoT) leading to meaningful data and more effective services. Long-Range Wide Area Network (LoRaWAN) is a low-power communications protocol specifically designed for the IoT ecosystem. In this protocol, the RF signals used to communicate between IoT end devices and a LoRaWAN gateway (GW) can be used for communication and localization simultaneously, using distinct approaches, such as Received Signal Strength Indicator (RSSI) or Time Difference of Arrival (TDoA). Typically, in a LoRaWAN network, different GWs are deployed in a wide area at distinct locations, contributing to different error sources as they experience a specific network geometry and particular environmental effects. Therefore, to improve the location estimation accuracy, the weather effect on each GW can be learned and evaluated separately to improve RSSI-based distance and location estimation. This work proposes an RSSI-based LoRaWAN location estimation method based on Edge-AI techniques, namely an Artificial Neural Network (ANN) that will be running at each GW to learn and reduce weather effects on estimated distance. Results have shown that the proposed method can effectively improve the RSSI-based distance estimation accuracy between 6% and 49%, and therefore reduce the impact of the environmental changes in different GWs. This leads to a location estimation improvement of approximately 101 m.

Keywords: IoT · RSSI · LoRaWAN · Localization · Edge-AI

1 Introduction

Shortly, the Internet of Things (IoT) will be the main part of many industrial and non-industrial systems [1]. The basic and essential required technology for the proper adoption of IoT is spatial data gathering. Therefore, localization techniques are an important feature for the next generation of IoT systems.

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The most commonly used approach for outdoor localization is based on Global Navigation Satellite Systems (GNSS). Global Positioning System (GPS) is one of the GNSS methods and provides a typical location estimation accuracy between 10 and 100 m [2].

Other outdoor localization methods designed for IoT-based systems should be according to their fundamental limitations. Important limitations of these systems include low power consumption and low cost [3]. These criteria are not fulfilled by GNNS systems—such as GPS, GLONASS, or GALILEO—because its chips are rather expensive and power-hungry, not addressing the cost and autonomy key criteria that IoT-based systems demand. As a result, IoT end devices should consume additional power to send their location information to a cloud-based server using an additional communication radio that also demands additional power to communicate. According to mentioned GNNS drawbacks, it is not a favorable solution for the localization of IoT-based systems.

Wireless-based technologies can also be used for localization [4]. In this approach, location estimation is determined by using different features of the wireless signals transmitted by the IoT end devices, such as Received Signal Strength (RSS) or Time Difference of Arrival (TDoA), among others. In this case, wireless signals can be used for both positioning and communication at the same time. However, the performance of these different techniques in Wireless-based localization is highly related to signal availability (coverage) and network geometry (DoP - dilution of precision).

IoT systems can be deployed over a wide area and the communication range between devices and network elements should be extended to guarantee high availability. Long-range communication technologies are composed of cellular technologies (5G, 4G/LTE) and Low-Power Wide-Area Network (LPWAN) technologies. As major disadvantages, cellular technologies present a higher operational cost, due to more complex hardware and the use of licensed spectrum, which also compromises its ecosystem development [5].

On the other hand, LPWAN provides long-range communication among IoT end nodes and servers with low cost and low power consumption. LPWAN is the best option to provide high geometry communication ability for IoT systems. There are three main LPWAN technologies: NB-IoT, Sigfox, and LoRaWAN. NB-IoT works in licensed spectrum and Sigfox coverage is provided by member companies. So, NB-IoT and Sigfox do not provide the ability to create private networks for customized deployment. Despite NB-IoT and Sigfox, LoRaWAN works in a license-free spectrum and it provides the possibility to establish a private network for IoT systems [6].

The star topology of LoRaWAN network architecture is shown in Fig. 1, where IoT end devices communicate throw LoRaWAN Gateways (GWs). LoRaWAN GWs gather the transmitted IoT end node packets and their RF signal features (RSS, SNR, SF, etc.), which may be used for Quality-of-Service (QoS) assessment and other third-party applications, such as for end-device localization. Next, LoRaWAN GWs sent the collected data to the LoRaWAN network server. The LoRaWAN network server receives the RF signal features of each end device transmitted through different GWs and sends them to the LoRaWAN application server. Finally, the application server estimates the end device localization by using the estimated distances. Range estimation is determined by the received signal features obtained from distinct GWs.

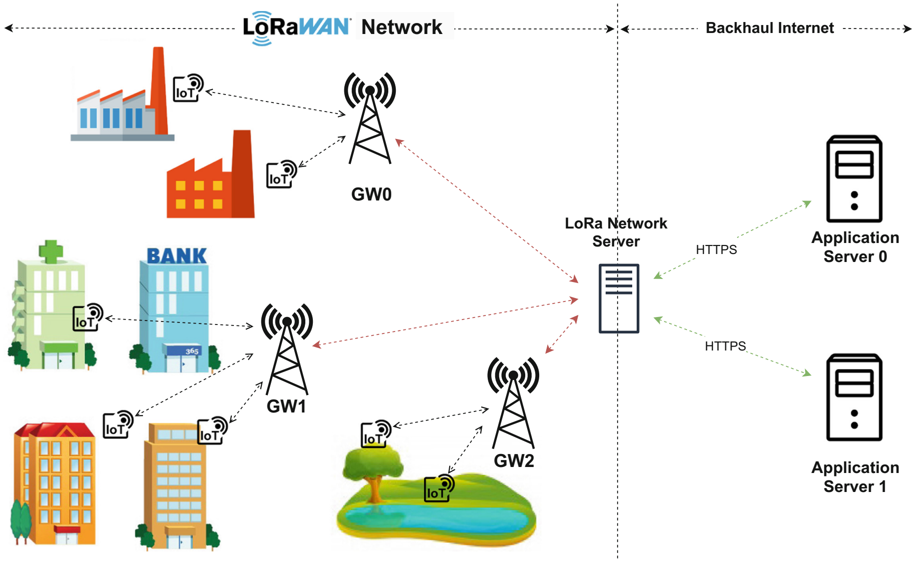

Fig. 1. LoRa network architecture.

As shown in Fig. 1, different LoRa GWs are placed in different locations. Different locations lead to different error sources since the GWs are affected by their surrounding environment. Therefore, to improve the location estimation accuracy, the environmental conditions that impact the distance estimation accuracy at each GW should be learned and evaluated separately. However, generating and sending information about each GW condition to the LoRaWAN network server can lead to a localization delay and consume a huge amount of bandwidth and energy from the network. To solve this problem, we propose a method to improve the RSSI-based LoRaWAN ranging estimation accuracy using edge computing. Edge computing follows a decentralized architecture [8], providing computation capabilities at the network edge. So, it leads to real-time data analysis, low operational cost, high scalability, reduced latency, and QoS improvement.

In this paper, we focus on the RSS-based localization principle. RSS-based localization methods are well-known, but when used in a changing environment, they can lead to poor estimation accuracies. These environmental-induced errors include multipath, non-line of sight (NLoS), wide-area effects, multi-floor effects, human-body effects, weather effects, and signal variations [7]. To improve localization accuracy, it is important to improve the distance estimation errors, which may be done by mitigating the environmental changing effects and its related errors in the ranging estimation stage, by introducing an Edge-AI learning stage to increase the accuracy in the distance estimation between IoT end devices and LoRaWAN GWs. Thus, the proposed method focus on the improvement of the ranging estimation based RSSI and an ANN algorithm to learn different weather situations on the received signal by different GWs. We evaluate the accuracy of this algorithm for large real-world areas.

The remainder of this document is organized as follows: Sect. 2 presents the related works; Sect. 3 introduces the proposed method for improving RSSI-based LoRaWAN localization; Sect. 4 describes the evaluation of the proposed method and puts forward a discussion around the results achieved. Lastly, in Sect. 5 the main conclusions are undertaken, and future work guidelines are presented.

2 Related Works

The localization problem has a long history in different application domains and several works have been put forward to achieve increased accuracy in low-cost GNSS-free positioning systems. In [7], Li et al. demonstrate the evolution of location-based services. GNSS-based systems are the most common for outdoor localization [9], but they are not a suitable solution for IoT applications due to higher cost, higher power consumption, and consequently low autonomy. On the other hand, LoRaWAN based localization methods are becoming popular for low-cost outdoor localization in the IoT ecosystem. They can be divided into three categories: 1) time-based, 2) path-loss and RSSI-based, and 3) fingerprint-based localization methods [10]. In this section, a brief overview of the workflow of LoRaWAN localization methods is provided.

Time of Arrival (ToA), Time Difference of Arrival (TDoA), and Round-Trip Time of Flight (RToF) are three time-based localization methods [11]. In ToA-based localization, the signal propagation time is used for distance estimation. TDoA determines the IoT end node distance by measuring the time difference at the arrival of signals. RToF measures the signal propagation round-trip time to estimate the distance between GW and IoT devices. Legacy localization methods use triangulation for location estimation and need precise synchronization between the network elements (ToA-based) or at least between the GWs (TDoA-based) and the accuracy of estimated location is highly dependent on it. So, time-based methods can lead to more complex hardware which impacts not only the end-device cost but also its autonomy [12].

RSSI and path-loss modeling is a commonly used method in LoRaWAN localization. In this approach, the received signal strength is collected and the path loss is computed in the GW, being used for the distance estimation between the IoT end device and the GW. RSSI lacks high accuracy duo to signal multipath and fading. To overcome these problems, a high number of RSSI readings is needed [13]. There are many different methods in this category [14–16]. In [14,15], authors used RSSI for location estimation in which assumes a well-known and measured path loss of the area. In [16], authors adopt LoRaWAN for Search and

Rescue operations. They have first characterized the LoRa path loss in three mountain scenarios. Then, they developed a localization algorithm that can be applied to estimate the position of injured persons by using known path loss and received RSSI. Authors in [14,17] realized that location estimation error rapidly increased because of the GWs noise. So, they propose GWs selection strategies for RSSI-based outdoor localization.

Fingerprint-based localization can be described in two stages: 1) learning stage (offline) and 2) localization stage (online). In the learning stage, various signal features in different places of area are collected and stored as a dataset. In the localization stage, the location estimation is performed by using a stored dataset. There are three different categories in the Fingerprint-based localization method: Visual Fingerprint, Motion Fingerprint, and Signal Fingerprint [18]. In [19], authors aims to provide accurate localisation in an urban LoRa network, using an ANN-based fingerprinting approach. In [20], authors studied various regression and machine learning models on received RSSI to accommodate the variability of factors for ranging estimation by using fingerprint. Authors in [21] mentioned it is not feasible work only with labelled samples in an outdoor environment. So, they proposed a semi supervised deep neural network for location estimation in LoRa. In [10], the authors proposed a LoRa signal-based positioning method that uses a fingerprint algorithm. They estimated the locations using probabilistic means based on three different algorithms that use interpolated fingerprint RSSI maps.

The weather condition is an environment error source that leads to location estimation error. Several works have evaluated the impact of meteorological conditions on packet reception, including the impact of weather conditions, and humidity [22]. In [23], authors analyze different weather situations on received signal strength. They mentioned that the RSS is strong during the day when the solar radiation is high.

Different GWs in LoRaWAN can settle in various places. Various places in a large area can experience distinct weather situations at the same time. Therefore, different GWs should evaluate the received signals based on their specific condition. For this purpose, Edge-AI can provide the required facilities and effectively improve the range measurements. Moreover, by taking advantage of edge computing we are bringing computation and storage to the edge of the network, near to where the data originates yielding reduced network load and better performance of services [24]. In this paper, the advantages of using Edge-AI for range estimation improvement in LoRaWAN are evaluated.

3 Proposed Method

In this section, a short overview of the basic principles for distance prediction based on RSSI is put forward, followed by the description of the proposed method for the improvement of RSSI-based ranging using Edge-AI and environmental data for distance estimation.

3.1 RSSI-Based Distance-Loss Modeling

RSSI-based distance-loss modeling is the simplest and widely used method for distance prediction. Typically, these methods take advantage of simple and well-known path-loss modeling, where each receiver (LoRa GW) measures the received signal strength of a pre-determined transmitted power from a sender (IoT end device). The RSSI value at each GW can then be used to estimate the distance between the GW and IoT device using the path-loss model equation, which enables us to estimate the distance between transmitter and receiver, as presented by the Eq. 1:

$$RSSI = -10nlog_{10}(d) + A \tag{1}$$

where n is the path-loss exponent of the communication channel which varies depending on specific environmental conditions, and A is the RSSI value at a reference distance from the receiver. In this case, both n and A are environmental-dependent and can change during time, as outdoor atmospheric conditions modify. In addition, the measured RSSI is prone to noise and interference, which can lead to large errors in distance estimation. Typically, the strength of the received signal has three main contributions. The first and main contribution is the sender signal power that can follow different path loss models. The second part is large-scale fading caused by shadowing and the last part is small-scale fading caused by different copies of the transmitted signal. Several environmental factors, contribute as error sources in the propagation of the signal between the transmitter and the receiver. The path-loss model previously introduced averages these contributions in a rough approach and does not consider any dynamic changes in the environmental conditions. Moreover, GWs are installed in various and environmentally distinct places, on top of a building, near a river, with distinct heights. These particular setup conditions are known to affect the distance-loss model and lead to transient changes in the propagated signal which impact the distance estimation process due to the omnipresence of these environmental-related error sources.

In the next subsection, the proposed method for weather effect reduction in RSSI-based distance estimation is proposed.

3.2 Distance Estimation Improvement Method

To improve distance estimation, the inclusion of the weather conditions will be considered and an ANN algorithm is adopted. ANN is an information processing system that mimics the human brain. It consists of many interconnected processing nodes (neurons) collaborating to solve a specific task. ANN is composed of three basic blocks: i) ANN is feed by input data as vector data; ii) ANN generates data and compares the generated data with the desired output; and iii) ANN alters the weights of neural network connections for a better approximation of the output.

The proposed method consists of three main steps: data gathering, system training, and system test. In the first step, data gathering, each GW is equipped with two sensors: a temperature sensor and a relative humidity sensor. In addition, the GWs receive other relevant weather information from the LoRaWAN network server periodically. When the GW receives data from the IoT end devices, it collects and registers RSSI and the weather information for each received signal. These values are fed as an input vector into the ANN. In the second step, the ANN obtains the best weights for the neural network connections to improve the approximation of the output. In this step, the real distance between the IoT end devices and GW is fed as an expected output to the ANN. In our system, four different types of ANN have been considered: a) Multilayer Perception (MLP) with one hidden layer; b) MLP with two hidden layers; c) Feed-Forward Artificial Neural Networks; and d) Radial Basis Function (RBF) network. The number of MLP neurons is considered equal to 20. MLP and Feed-Forward with two layers have 15 and 8 neurons, respectively. MLP with two hidden layers and Feed-Forward are both shown in Fig. 2.

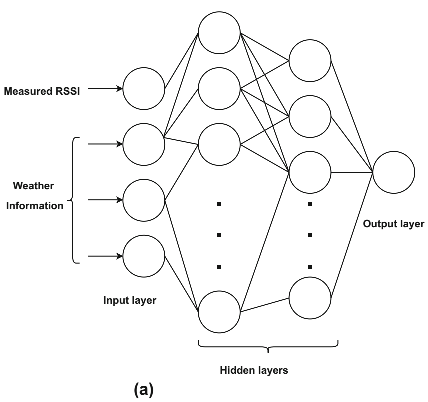

Fig. 2. ANN structure: a) MLP with two hidden layers, b) Feed-Forward neural network with two hidden layers.

In the last step, the GWs send the estimated distance to the LoRaWAN network server—which merges all the estimated distances coming from all the GWs—and sends them to the LoRaWAN application server to compute the IoT end devices localization [25].

4 Method Evaluation

In this section, the effect of weather changes on the accuracy of the predicted distance by the GWs and predicted location by LoRa application server is evaluated. To this purpose, we first overview and describe the used datasets in the evaluation of the proposed approach, followed by the presentation and discussion of final the evaluation results.

4.1 LoRaWAN Dataset

Two publicly available datasets have been used to create the dataset used in the final evaluation. The first is LoRaWAN dataset provided by [26]. This LoRaWAN dataset aims to provide the global research community with a benchmark tool to evaluate fingerprint localization algorithms in large outdoor environments with various properties. It is a large dataset of LoRaWAN messages obtained in the city center of Antwerp together with network information, such as the receiving time of the message, base station IDs', and RSSI. The collection methodology is presented in detail in [26]. A total of 20 cars of the Belgian postal services were equipped with low-power devices communicating via LoRaWAN with a central server. At the same time, the location of the car, as estimated by a GPS device, was also reported. In this dataset, the GPS estimates are considered as the spatial ground truth. For the evaluation of our method, LoRaWAN messages transmitted during four days in January 2019 have been adopted (14th, 15th, 17th, and 18th). This period contains 10423 messages that have been received by different gateways. The GWs position in Antwerp is shown in Fig. 3, being the GWs evaluated identified in red.

The second one is the weather information dataset provided by [27]. This dataset provides different weather information about different cities including temperature, relative humidity, wind speed, etc. To evaluate the proposed method, the weather information of the city of Antwerp has been included in the LoRaWAN dataset. The included weather information comprises temperature, relative humidity, and weather condition. Different weather conditions (fogy, rainy, passing clouds, etc.) are denoted and added to the dataset by a specific integer number, raising from 1 to 8, respectively.

4.2 Distance Estimation Results

As mentioned, GWs in different places have distinct environment error sources and each one of these error sources has a specific influence on distance estimation accuracy. To illustrate this issue, three GWs (i.e. GW2, GW193, and GW223) in diverse places were considered and distance prediction accuracy assessment has been provided in two distinct scenarios: 1) using only RSSI data; and 2) using RSSI and outdoor environmental data (i.e. humidity, temperature, and weather condition). GW2 is surrounded by buildings, GW 193 is near the lake, and GW223 is near a park. As mentioned, four types of neural networks are considered (MLP with one hidden layer, MLP with two hidden layers, Feed-Forward artificial neural networks, and RBF network) for distance prediction, and the model with less distance prediction error is then adopted. To make a reliable evaluation, k-fold cross-validation (k is equal to 10) was applied during the simulation. Then, the average distance prediction error is reported.

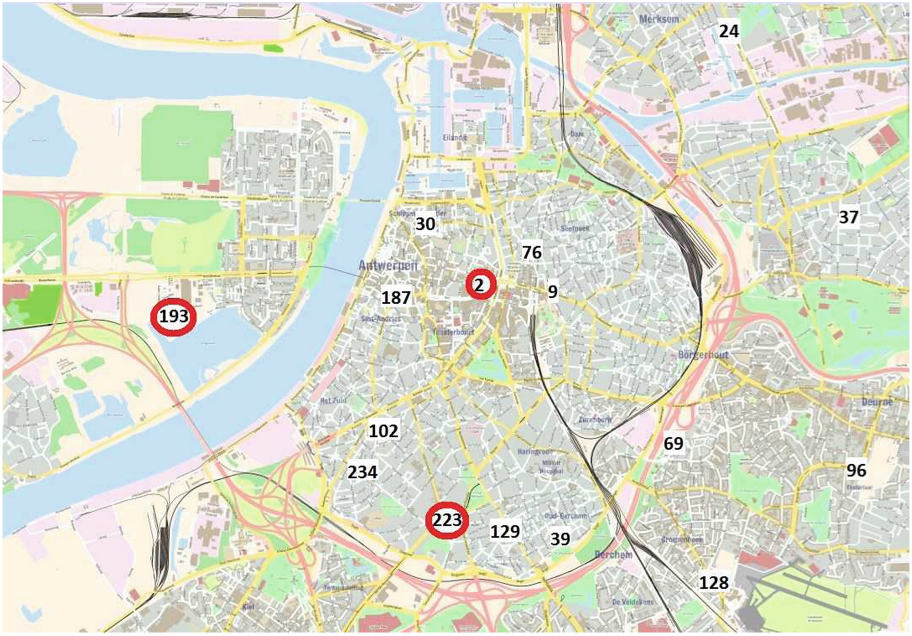

Fig. 3. LoRa gateways positions in Antwerp. (Color figure online)

The simulation is performed on a laptop simulating an edge device. The laptop has a Core-i3 processor with CPU and RAM equal to 2.4 GHz and 4 GB respectively and the clock Precision is equal to 1.0e−03. The simulation is done using Matlab and the relative computational cost has been evaluated.

The results obtained for GW2, GW193, and GW223, are presented for both scenarios in Figs. 4, 5, and 6, respectively.

As shown in Fig. 4, the distance prediction accuracy of GW2 by using only RSSI data is less than 400 m for 52% of the cases. To evaluate the weather effect on distance prediction accuracy of GW2, we used a Feed-Forward neural network that leads to better performance (Levenberg-Marquardt as training algorithm). By considering the weather factor, the distance prediction accuracy increases to 68% in 52% of the cases. Therefore, the weather consideration in this gateway leads to a 16% accuracy increment. In addition, by including the weather conditions, a distance prediction error of more than 600 m has decreased 10% (from 27% to 17%).

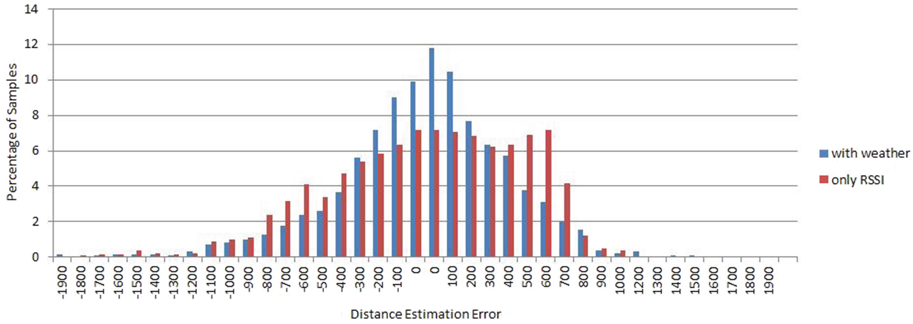

Fig. 4. Distance Prediction Error of LoRa GW2.

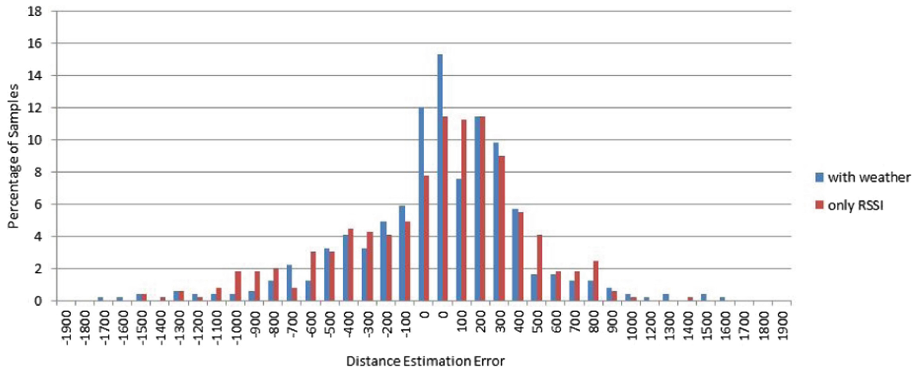

Fig. 5. Distance prediction error of LoRa GW193.

As depicted in Fig. 5, the distance prediction accuracy of GW193 by using only RSSI is less than 400 m for 64% of data. To evaluate the weather effect on RSSI, MLP with one hidden layer has better performance (Levenberg-Marquardt as training algorithm). By considering the weather effect, the distance prediction accuracy increases to 70%. Hence, the weather error in this gateway leads to a decrease in accuracy of 6%. In addition, by including the weather conditions, a distance prediction error of more than 600 m has reduced 4% (from 19% to 15%).

As illustrated in Fig. 6, the distance prediction accuracy of GW223 by using RSSI is less than 400 m for 14% of the data. By considering the weather effect, the distance prediction accuracy increases to 63%. Therefore, the weather error in this gateway leads to an accuracy reduction of 49%. In addition, by including the weather conditions, a distance prediction error of more than 600 m reduced 20% (from 47% to 27%). Training and validation curves of GWs are shown in Fig. 7.

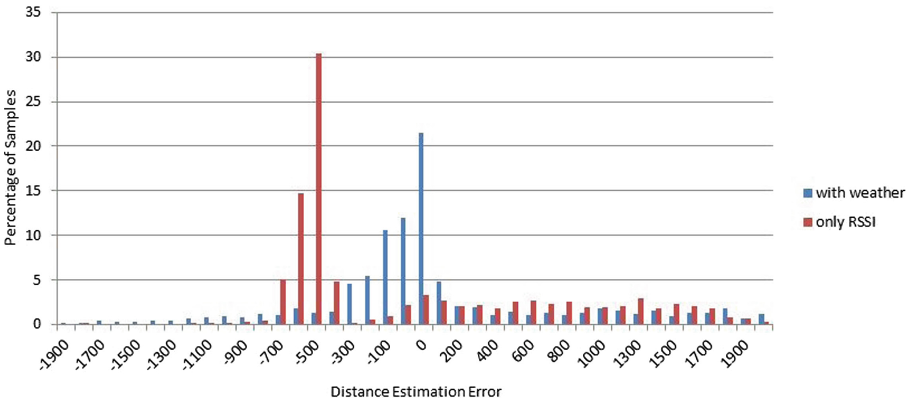

Fig. 6. Distance prediction error of LoRa GW223.

By results observation, by considering the weather situation the RSSI-based distance prediction improves but the improvement rate varies for different GWs. In addition, the distance prediction error of more than 800 m means an environment error source existence that should be considered for the improvement of distance prediction accuracy.

4.3 Localization Estimation Results

To evaluate the location estimation accuracy, two scenarios for 32 different messages of objects, received by all three gateway, are investigated. In the first scenario, each gateway sends the measured RSSI of the sender to the LoRa network server. Then, the LoRa network server merges the received measured RSSI from the different gateway and sends it to the LoRa application server to compute the location of the objects. In the second scenario, each gateway computes the distance of the objects based on the measured RSSI after weather effect mitigation. Then, the LoRa gateway sends the computed distance to the LoRa network server. LoRa network server merges and sends them to the LoRa application server. LoRa application server computes the object location based on the computed distance. The location estimation error of these two scenarios is shown in Fig. 8. The first scenario has a mean error of 624 m and the second scenario has a mean error of 522 m. So, The proposed method (second scenario) leads to a location estimation improvement of approximately 101 m.

4.4 Edge-AI Deployment

Based on expressed results, the weather situation has a distinct effect and a considerable impact on the GWs, based on their locations. For applying these effects, there are two different methods. First, each GW can be equipped with various sensors to determine their environmental condition followed by transmission to the LoRaWAN application server throw the LoRaWAN network server.

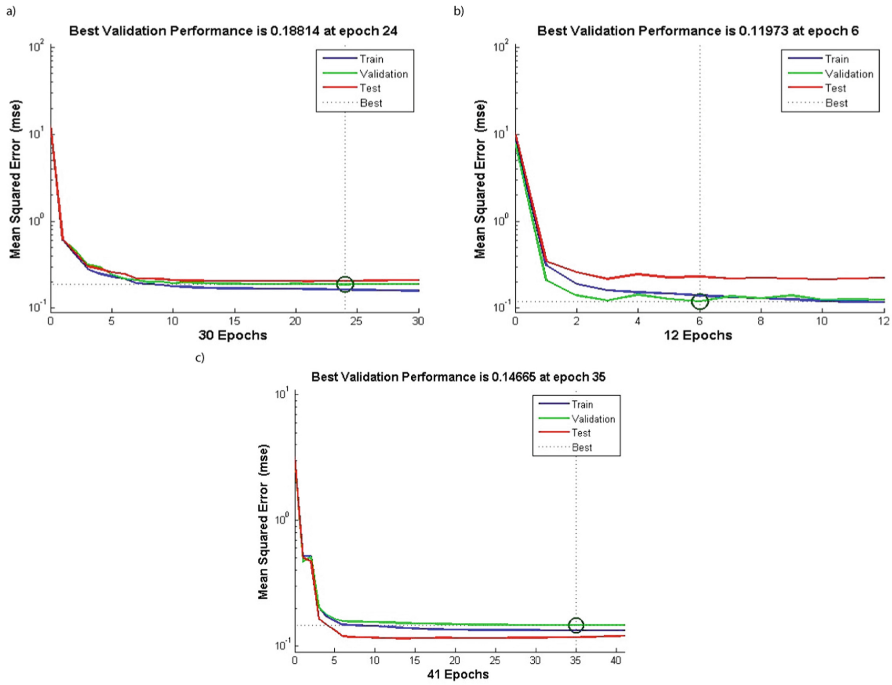

Fig. 7. Training and validation curves of GWs: a) GW2, b) GW193, and c) GW223.

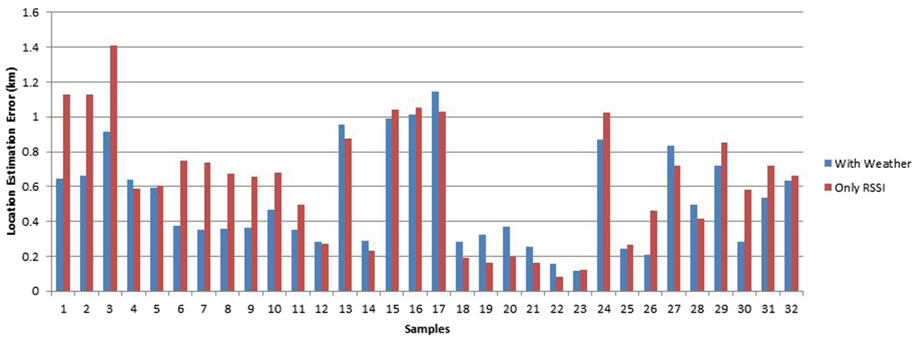

Fig. 8. Location estimation error.

The LoRaWAN application server determines IoT end device distances from GWs by the received information. By increasing the number of IoT end devices, this method fails in fulfilling latency requirements due to long response times. In addition, network data usage will increase with the increase of IoT end devices.

Second, different GWs compute the IoT end device distance by using measured RSSI and their environmental condition. This method can be implemented by including Edge-AI at the GWs. Edge-AI provides computational capabilities at the LoRaWAN GWs, which are physically close to the end devices. This can lead to low latency results and ranging estimation improvement.

The computational cost of the second method can be expressed in two ways. First, the training step and test are provided in the edge device. In this case, it is composed of 413 structs. Second, the training step is done in the server and the learned net is transferred to the edge for evaluation. In this case, it is composed of 108 struts.

5 Conclusion and Future Work

Various environment error sources affect distance estimation. As GWs are placed in distinct places, they are impacted by their environmental surroundings differently. In this paper, we studied the problem of various effects of weather situations on different GWs in a LoRaWAN network. The problem was defined to improve RSSI-based distance estimation in LoRaWAN networks. For this purpose, we proposed an RSSI-based method to improve range estimation in LoRaWAN networks using Edge-AI. The proposed method improved the estimated distance by adopting ANN for weather effect learning in each GW. Numerical results demonstrated the distance improvement performance of our proposed scheme over the basic method based on RSSI. Our proposed method leads to decrements between 4% and 20% of the distance prediction error of more than 600 m and increment between 6% to 49% of the distance prediction error of less than 400 m. This improved estimated distance leads to a location estimation improvement of approximately 101 m. For future work, we are going to investigate the weather effect on other signal features and evaluate its impact on location estimation.

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