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LoRa RSSI based Outdoor Localization in an Urban Area Using Random Neural Networks

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Abstract. The concept of the Internet of Things (IoT) has led to the interconnection of a significant number of devices and has impacted several applications in smart cities' development. Localization is widely done using Global Positioning System (GPS). However, with large scale wireless sensor networks, GPS is limited by its high-power consumption and more hardware cost required. An energy-efficient localization system of wireless sensor nodes, especially in outdoor urban environments, is a research challenge with limited investigation. In this paper, an energy-efficient end device localization model based on LoRa Received Signal Strength Indicator (RSSI) is developed using Random Neural Networks (RNN). Various RNN architectures are used to evaluate the proposed model's performance by applying different learning rates on real RSSI LoRa measurements collected in the urban area of Glasgow City. The proposed model is used to predict the 2D cartesian position coordinates with a minimum mean localization error of 0.39 m.

Keywords: IoT; LoRaWAN; RSSI; Localization; RNN

1 Introduction

IoT connected devices are projected to increase exponentially [1], and this is expected to trigger different smart applications in various domains such as healthcare, agriculture, transportation among others. Low Power Wide Area Networks (LPWAN) such as Long-Range Wide-Area Networks (LoRaWAN) are potential reliable low power connectivity solutions to large-scale IoT networks [2]. Moreover, location-aware applications such as Remote Health Monitoring (RHM) is one of the promising smart applications of LoRaWAN [3]. Additionally, an accurate localization system for sensor nodes is crucial, particularly in applications where locating end devices is critical. A typical outdoor localization method in LoRa networks is the Time Difference of Arrival (TDoA) technique. However, this method performs well in open environments and poorly in harsh urban areas. In comparison, WiFi and Bluetooth RSSI fingerprint based techniques have been successfully applied for indoor localization [4]. While, end device fingerprint

localization based on LoRaWAN RSSI characteristics is a research topic yet to be thoroughly investigated, both in indoor and outdoor environments.
Furthermore, RNN has recently been used to create several resilient models with significant results [24]. Currently, no one has reported RNN algorithms applied in end device localization models for IoT wireless sensor nodes. In this paper, we use real test LoRaWAN RSSI data collected in the urban area of Glasgow City to develop a localization model based on LoRaWAN RSSI characteristics using RNN.
End device localization is vital in location-aware IoT applications whereby a sensor node needs to be accurately located for emergency or maintenance services. RSSI fingerprint localization methods involve mapping RSSI values to corresponding X, Y Cartesian 2D position coordinates [32]. Moreover, RSSI fingerprint localization approaches have been proposed for accurate localization models in the literature using GNSS, Bluetooth, and WiFi wireless technologies and successfully implemented but all with significant drawbacks and limitations. In Addition, the following challenges are among the issues limiting the performance of existing RSSI fingerprint techniques for effective end device localization:

1. Fingerprint data maps are affected by changing environments.
2. Strong fingerprint databases are needed.
3. Manpower is needed for creating fingerprint databases.
4. Non-linearity challenge between end nodes and target gateways.
5. High power-consumption and cost.
6. Complicated infrastructure layout.

Studies using LPWAN for sensor node localization are present in literature, however, frequently limited to specific settings such as a small area or fixed end nodes. Furthermore, no other work has used RNN for LoRaWAN based node localization models (to the best of our knowledge). Therefore, this work aims at using RNN algorithms to develop a resilient novel system to improve location prediction accuracy compared to the existing RSSI fingerprint approaches. The main contributions of this paper are summarized as:

- Development of novel RNN based models for accurate LoRa end device localization.
- Real test data sets collected in Glasgow's urban city are used to train and test the developed localization model with a different number of hidden neurons.
- The performance of the developed RNN based localization model is evaluated, and improved accuracy is achieved by training and testing various RNN network architectures using different learning rates.

This paper is organized as follows: Section II introduces LoRa, and LoRaWAN. Section III discusses the related work. Section IV gives the details of the methodology and the procedures used. Section IV presents the obtained results with the performance analysis of the developed model. Finally, Section VI gives conclusions and future work directions.

2 LoRa and LoRaWAN

The invention of low power wide-area network technologies like LoRaWAN, and other potential network enablers for the dense IoT networks, came as a perfect solution for large scale IoT smart applications. LoRa is a physical layer with the Chirp Spread Spectrum (CSS) modulation technique operated by Semetch within the license-free spectrum, whereas LoRaWAN is the connection protocol stack of the wide-area network of LoRa architecture on the MAC layer [6]. A LoRaWAN network is made up of LoRa end devices connected in a star topology that sends information to one or multiple LoRaWAN gateways. Therefore, the gateways that send the received message to a network server along with a recorded unique message's metadata information, as shown in Figure 1. Thus, this metadata information enables localization in LoRaWAN networks, whereby gateways serve as anchor points to determine position coordinates. TDoA algorithms use timestamps at which different gateways receive the same message, whereas the most critical metric for Fingerprinting is RSSI. Also, the more gateways that can receive the same message, the more accurate a localization algorithm is in any of the methods [8]. Furthermore, the Spreading Factor (SF) is a LoRa critical parameter that affects localization accuracy, whereby lower SF limits the transmission range of LoRa devices. Consequently, fewer gateways receive the same message [7].

3 RELATED WORK

This section presents an overview of existing RSSI Fingerprint localization techniques, Random Neural Networks, and Gradient Descent Algorithm (GDA).

3.1 Overview of RSSI Fingerprint Localization Methods

Different algorithms using RSSI fingerprinting localization exist in literature using various wireless technologies. However, existing studies frequently investi-

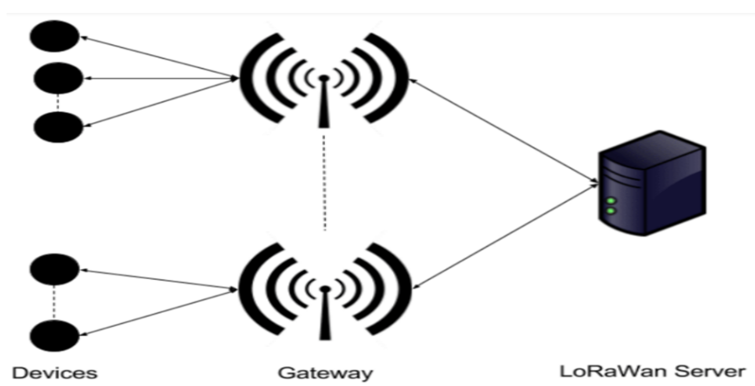

Fig. 1: LoRaWAN network architecture [6]

gated mostly indoor environments due to the training phase's many data. Furthermore, limited studies are available for localization analysis in outdoor environments, mainly due to the hard work involved in collecting data. WiFi has been used widely in fingerprint localization [9], [10], [11], and [12] whereby a smartphone can be used to record its RSSI and estimate its location using the web. The authors make a comparative performance analysis of different wireless technologies based on RSSI localization in [13]. Research studies using LoRaWAN in fingerprint localization are also available in literature [14], [15], [16], [17]. Moreover, Choi. W et al. in [18] used LoRa for positioning using three fingerprint algorithms and confirmed LoRa to be effective with the average accuracy of 28.8 m for the three algorithms. Aernouts. M et al. in [19] presented fingerprint localization data sets for LoRaWAN and Sigfox in large urban and rural areas with a mean estimation error of 398.40 m. Similarly, the authors in [20], [21], [22] also investigated LoRa RSSI based fingerprint localization algorithms with significant estimations.

3.2 Random Neural Networks

RNN has recently been used to create resilient models with significant results. Application in Heating, Ventilation, and Air Conditioning (HVAC) systems by Javed. A et al. in [23], [24], [25], energy prediction of non-occupied buildings by Ahmad. J et al. in [26], communication systems, image classification, processing, pattern recognition by Simonyan. K and Zisserman [35], whereas intrusion detection systems were developed and analyzed by Ul-Haq Qureshi. A et al. in [27], [28], [29]. Nonetheless, no one has reported RNN algorithms applied in end device localization models (to the best of our knowledge).

RNN is a unique class of ANN developed by Gelenbe [30], consisting of directed N multiple layers of connected neurons that exchange information signals as impulses, using a potential positive (+1) for excitation and a negative (-1) for inhibition signals to the receiving neuron. The potential of each neuron i at time t is represented by a nonnegative integer $K_i(t)$. The neuron i is in excited state if $K_i(t) > 0$ and it is in idle state if $K_i(t) = 0$. If neuron i is excited, it forwards an impulse signal to another neuron j at the Poisson rate r_i. The forwarded signal can reach neuron j as an impulse signal in excitation or inhibition with probabilities $p^+(i,j)$ or $p^-(i,j)$ respectively. Furthermore, the transmitted signal can leave the network with a probability mathematically defined in [26] by the following formulas:

$$c(i) + \sum_{j=1}^{N} p^+(i,j) + p^-(i,j) = 1, \forall i, \tag{1}$$

$$w^+(i,j) = r_i p^+ + (i,j) \geq 0, \tag{2}$$

Equally

$$w^{-}(i,j) = r_i p^{-} + (i,j) \geq 0. \tag{3}$$

Combining Equation 1, 2 and 3

$$r(i) = (1 - c(i))^{-}1 \sum_{j=1}^{N} [w^{+}(i,j) + w^{-}(i,j)] \tag{4}$$

The transmission rate between neurons in Equation 4 is $r(i)$, and is defined as $r(i) = \sum_{j=1}^{N} [w^{+}(i,j) + w^{-}(i,j)]$. While "$w$" determines the matrices of weight updates from neurons, it is always positive as it is a product of transmission rates and probabilities.
In RNN based models, if a signal arrives at neuron (i) with a positive potential, it is denoted by Poison rate $\Lambda(i)$, whereas a signal with a negative potential arrives at Poisson rate $\lambda(i)$. Therefore, for every node "i" the output activation function for that neuron is given by:

$$q(i) = \frac{\lambda^{+}(i)}{r(i) + \lambda^{-}(i)}, \tag{5}$$

whereby

$$\lambda^{+}(i) = \sum_{j=1}^{n} q(j) r(j) p^{+}(j,i) + \Lambda(i), \tag{6}$$

with

$$\lambda^{-}(i) = \sum_{j=1}^{n} q(j) r(j) p^{-}(j,i) + \lambda(i). \tag{7}$$

More details about RNN are in [26].

3.3 Gradient Descent Algorithm

Gradient Descent (GD) is a first-order iterative optimization algorithm widely used for training by different researchers. It is used to minimize the cost function whereby the error cost function is given by:

$$E_p = \frac{1}{2} \sum_{i=1}^{n} \gamma_i (q_j^p - q_j^p)^2, \gamma_i \geq 0 \tag{8}$$

whereby $\gamma \in (0,1)$ presents the state of output neuron i, likewise q_j^p is a real differential function whereas q_j^p is the predicted output value. As, per Equation 8, to find the local minima and reduce the error value of the error cost function, the relation between neurons y an z is considered, whereby weights $w^{+}(y,z)$ and $w^{-}(y,z)$ are updated by:

$$w_{y,z}^{+t} = w_{y,z}^{+(t-1)} - \eta \sum_{i=1}^{n} \gamma_i (q_j^p - y_j^p)[\partial q_i \partial w_{y,z}^{+}]^{t-1}, \tag{9}$$

also:

$$w_{y,z}^{-t} = w_{y,z}^{-(t-1)} - \eta \sum_{i=1}^{n} \gamma_i (q_j^p - y_j^p)[\partial q_i \partial w_{y,z}^{-}]^{t-1}. \tag{10}$$

The proposed RNN-LoRa RSSI based localization model is trained using GD, and the calculated weights and biases are updated to the neurons as the algorithm computes the error. More details about GD are found in [26].

4 Methodology

This section gives details about all the procedures used in data collection and developing our RNN-LoRa RSSI based localization model.

4.1 Real Test Measurements

Real test LoRa RSSI datasets were collected in Glasgow City for the training and testing of our developed RNN based end device localization models. Three LoRa SX1301-enabled Kerlink gateways were used to receive the same messages from a MultiTech systems' LoRaWAN mDot end device controlled by Raspberry Pi. The three gateways were at 30m on George More building in Glasgow Caledonian University, at 27m on James Weir building at the University of Strathclyde, and at 25m on top of Skypark building, respectively. The LoRa mote was used to collect data and transmit it to the three gateways simultaneously at a walking speed away from the gateways from different locations. Figure 2. Shows a Bing map with three LoRaWAN gateways, LoRa end device locations, and the path is taken for measurements. More details about the procedure used in our measurements are given in [31].

Data Normalization Our dataset's RSSI absolute values are large, which results in an unstable network due to large weights. Therefore, we scaled our dataset using the Min-Max Normalisation data pre-processing technique to the range of 0 to 1, using the following formula:

$$x_i = \frac{RSSI_i - \min(RSSI)}{\max(RSSI) - \min(RSSI)}, \tag{11}$$

where $RSSI = (RSSI_1, ..., RSSI_n)$ is the raw RSSI input values and $x_(i)$ is the resultant normalized data.

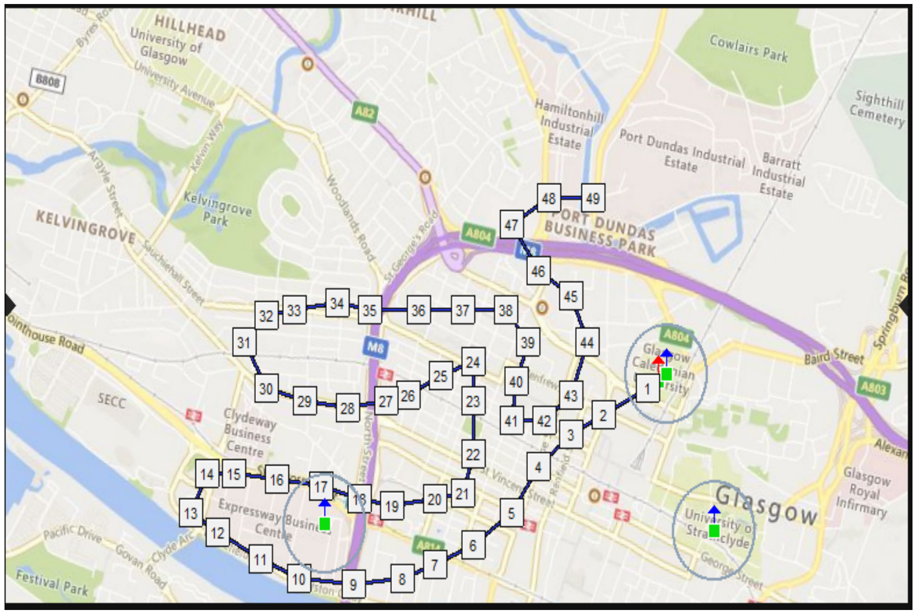

Fig. 2: Glasgow City Bing Map showing three LoRaWAN gateways, LoRa end device positions and the path taken for data collection

4.2 RNN-LoRa RSSI based Localization Model

End device localization using the RNN approach consists of directed multiple layers of connected nodes in a network. This network is used to develop a model that accurately maps the input to the output using historical data, and the model can then be used to output any desired unknown output. We used the RNN network to develop our proposed model that accurately maps the input RSSI values to the output Cartesian X, Y coordinates using real data measurements collected before, as presented in Figure 3. Then, the model is used to output any desired unkown position with minimum localization error. RNN learning GD algorithm that provides supervised training is considered for this research study. The RNN is trained to locate each end device in the network service area or grid, and then the trained network is extended further to predict the location of any other sensor nodes on the same network grid based on end-device LoRaWAN-RSSI fingerprints.

Using RNN, we develop RNN-LoRa RSSI-based Localization Model in MATLAB using fingerprint data set created from real measurements taken in Glasgow City with three LoRaWAN gateways. The dataset contains for every message transmitted by the moving end device, the RSSI value at each of the three gateways that received the message with ground position coordinates of the end device at every transmission. Furthermore, we recorded -200 as the RSSI value for every gateway that did not receive a particular message.

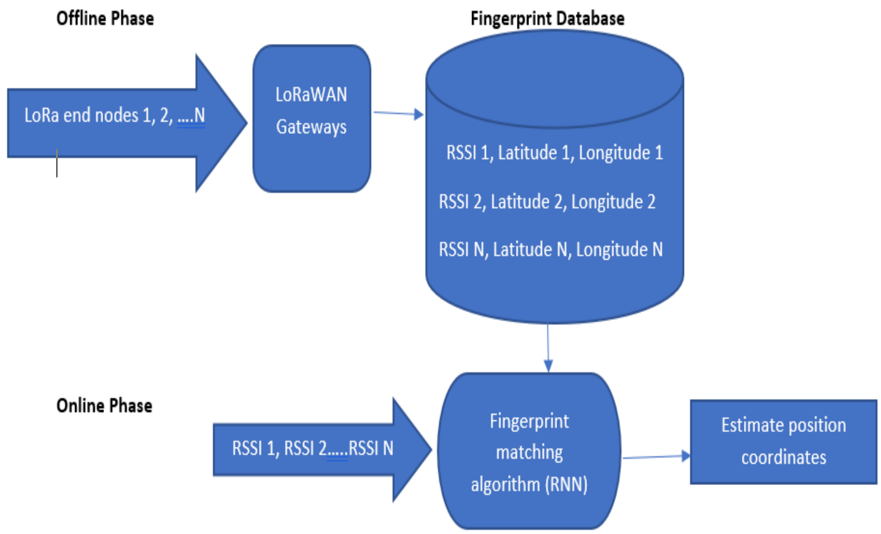

Fig. 3: RSSI Fingerprint Localization Approach

5 RESULTS AND PERFORMANCE ANALYSIS

In this section, various RNN architectures for a number of hidden neurons of 6, 12, and 18 were modelled and analysed with 0.01, 0.1, and 0.4 learning rates. Corresponding training and test results of mean localization errors are recorded. A minimum mean localization error of 0.39 m is obtained in a sample size of 1931 data points, whereby 80% of the dataset was used for training and 20% for testing the model with a minimum training mean square value of 0.005 m. The performance of the developed RNN based localization model is analysed using the average localization error (AE) defined as follows:

$$AE = \sum_{i=1}^{n} ((X_{real} - X_{pred})^2 + (Y_{real} - Y_{pred})^2)^{0.5} \tag{12}$$

Whereby (X_{real}, Y_{real}) is the real true pre-recorded position using GPS and (X_{pred}, Y_{pred}) is the predicted position of unknown location estimated by the LoRa RSSI based localization system developed using RNN. The total number of samples used in our localization dataset is given by n. Figure 4 presents results for mean localization error values for all the three RNN-LoRa RSSI based localization system architectures using 0.01, 0.1, and 0.4 learning rates. The results show that for the first system network architecture (RNN-1); increasing the learning rate from 0.01 to 0.1 improved localization performance by minimizing the mean localization error. However, increasing the learning rate further to 0.4

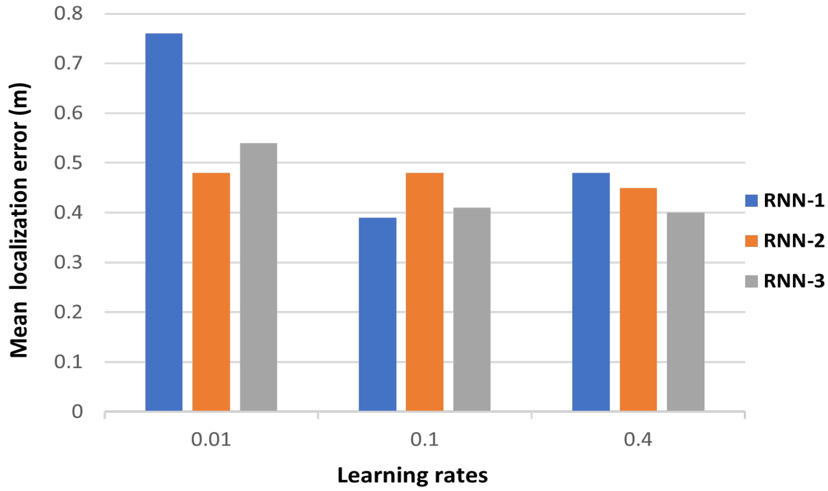

Fig. 4: Performance analysis between RNN based localization network architectures with different learning rates

led to an increase in the mean localization error. Hence, using 0.1 learning rate had the best performance, whereby only six hidden neurons were used.
For the second system architecture (RNN-2), increasing the learning rate from 0.01 to 0.1 increased the system's mean localization error whereas increasing the learning rate further to 0.4 decreased the error. Hence, using 0.01 learning rate had the best performance where twelve hidden neurons were used.
Likewise, for the third system architecture (RNN-3); eighteen hidden neurons were used, and the learning rate increased with the decrease in the mean localization error. Furthermore, three input neurons and two output neurons are considered for all the three RNN localization model architectures in our analysis. In general, our results show that the developed RNN LoRa RSSI based localization model performed best with a learning rate of 0.01 and when twelve hidden neurons were used. Also, increasing the number of hidden neurons does not significantly improve the performance of the system apart from when the highest learning rate of 0.4 was used.
A comparative performance analysis of localization accuracy of all analysed RNN based localization architectures with different learning rates is summarised in TABLE I.

According to our results, the developed RNN based localization models are reliable with significant minimum mean localization errors and outperform the conventional LoRa localization approaches reported by different researchers in literature [32], [8], [19], [33], and [34] with high accuracy for outdoor localization services.

Table 1: Performance of different RNN based localization architectures

Learning rates	**Mean localization error (m)**		
	RNN-1	**RNN-2**	**RNN-3**
0.01	0.76	0.39	0.48
0.1	0.48	0.48	0.45
0.4	0.54	0.41	0.40

6 CONCLUSION AND FUTURE WORK

In this study, we presented a LoRa RSSI based outdoor localization system using Random Neural Networks. Three RNN architectures are used to evaluate our localization model's performance using data collected in the urban area of Glasgow City, considering 0.01, 0.1, and 0.4 as learning rates. The proposed model performed best with a minimum mean localization error of 0.39 m. Moreover, the analyzed RNN based localization system architectures showed that increasing the number of hidden neurons does not improve the localization system's performance unless a high learning rate is used. Our results are significant with high-level accuracy for outdoor positioning in urban areas and give important insights for using LoRaWAN and RNN in localization systems. We plan to do a comparative performance analysis of our developed localization model to existing localization models found in literature.

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REFERENCES

[1] Statista Says a Five-Fold Increase in Ten years in Internet-Connected Devices by 2025 Will Significantly Increase the Internet's Promise of Making the World Connected,[online]Available:https://www.statista.com/ statistics /471264/iot-number-of-connected-devices-worldwide/(Accessed October 27, 2020).

[2] A. I. Ahmad, B. Ray, and M. Chowdhury, "Performance evaluation of loraWAN for mission-critical IOT networks," *Commun.Comput. Inf. Sci.*, vol. 1113 CCIS, pp. 37–51, 2019.

[3] J. Kharel, H. T. Reda, and S. Y. Shin, "Fog Computing-Based Smart Health Monitoring System Deploying LoRa Wireless Communication," IETE Tech.

Rev. (Institution Electron. Telecommun. Eng. India), vol. 36, no. 1, pp. 69–82, 2019.

[4] A. Poulose and D. S. Han, "UWB Indoor Localization Using Deep Learning LSTM Networks," Appl. Sci., vol. 10, no. 18, p. 6290, 2020.

[5] A. Javed, H. Larijani, A. Wixted, and R. Emmanuel, "Random neural networks based cognitive controller for HVAC in non-domestic building using LoRa," Proc. 2017 IEEE 16th Int. Conf. Cogn. Informatics Cogn. Comput. ICCI*CC 2017, pp. 220–226, 2017.

[6] Semtech, "LoRaWANspecificationv1.1." [Online]. Available:https://www.lora-alliance.org/technology. [Accessed October 27, 2020].

[7] S. Ghoslya, "All about LoRa and LoRaWAN." [Online]. Available:https://www.sghoslya.com.

[8] D. Bissett, "Analysing tdoa localisation in LoRa networks," Delft University of Technology, 2018.

[9] N. Abdul, K. Zghair, M. S. Croock, A. Abdul, and R. Taresh, "Indoor Localization System Using Wi-Fi Technology," Iraqi J. Comput. Commun. Control Syst. Eng., no. April, pp. 69–77, 2019.

[10] N. Hernández, M. Ocaña, J. M. Alonso, and E. Kim, "Continuous space estimation: Increasingwifi-based indoor localization resolution without increasing the site-survey effort," Sensors (Switzerland), vol. 17, no. 1, 2017.

[11] T. Janssen, M. Weyn, and R. Berkvens, "Localization in low power wide area networks using wi-fi fingerprints," Appl. Sci., vol. 7, no. 9, 2017.

[12] F. Zafari, A. Gkelias, and K. K. Leung, "A Survey of Indoor Localization Systems and Technologies," IEEE Commun. Surv. Tutorials, vol. 21, no. 3, pp. 2568–2599, 2019.

[13] S. Sadowski and P. Spachos, "RSSI-Based Indoor Localization with the Internet of Things," IEEE Access, vol. 6, pp. 30149–30161, 2018.

[14] H. Kwasme and S. Ekin, "RSSI-Based Localization Using LoRaWAN Technology," IEEE Access, vol. 7, pp. 99856–99866, 2019.

[15] M. Anjum, M. A. Khan, S. Ali Hassan, A. Mahmood, and M. Gidlund, "Analysis of RSSI fingerprinting in LoRa networks," 2019 15th Int. Wirel. Commun. Mob. Comput. Conf. IWCMC 2019, no. June, pp. 1178–1183, 2019.

[16] Y. C. Lin, C. C. Sun, and K. T. Huang, "RSSI Measurement with Channel Model Estimating for IoT Wide Range Localization using LoRa Communication," Proc. - 2019 Int. Symp. Intell. Signal Process. Commun. Syst. ISPACS 2019, pp. 5–6, 2019.

[17] E. Goldoni, L. Prando, A. Vizziello, P. Savazzi, and P. Gamba, "Experimental data set analysis of RSSI-based indoor and outdoor localization in LoRa networks," Internet Technol. Lett., vol. 2, no. 1, p. e75, 2019.

[18] W. Choi, Y. S. Chang, Y. Jung, and J. Song, "Low-power LORa signal-based outdoor positioning using fingerprint algorithm," ISPRS Int. J. Geo-Information, vol. 7, no. 11, pp. 1–15, 2018.

[19] M. Aernouts, R. Berkvens, K. Van Vlaenderen, and M. Weyn, "Sigfox and LoRaWAN datasets for fingerprint localization in large urban and rural areas," Data, vol. 3, no. 2, pp. 1–15, 2018.

[20] K. H. Lam, C. C. Cheung, and W. C. Lee, "LoRa-based localization systems for noisy outdoor environment," Int. Conf. Wirel. Mob. Comput. Netw. Commun., vol. 2017-Octob, pp. 278–284, 2017.

[21] A. A. A. Elsabaa, M. Ward, and W. Wu, "Hybrid localization techniques in lora-based WSN," ICAC 2019 - 2019 25th IEEE Int. Conf. Autom. Comput., no. September, pp. 1–5, 2019.

[22] K. H. Lam, C. C. Cheung, and W. C. Lee, "RSSI-Based LoRa Localization Systems for Large-Scale Indoor and Outdoor Environments," IEEE Trans. Veh. Technol., vol. 68, no. 12, pp. 11778–11791, 2019.

[23] A. Javed, H. Larijani, A. Ahmadinia, R. Emmanuel, M. Mannion, and D. Gibson, "Design and Implementation of a Cloud Enabled Random Neural Network-Based Decentralized Smart Controller with Intelligent Sensor Nodes for HVAC," IEEE Internet Things J., vol. 4, no. 2, pp. 393–403, 2017.

[24] A. Javed, H. Larijani, A. Wixted, and R. Emmanuel, "Random neural networks based cognitive controller for HVAC in non-domestic building using LoRa," Proc. 2017 IEEE 16th Int. Conf. Cogn. Informatics Cogn. Comput. ICCI*CC 2017, pp. 220–226, 2017.

[25] A. Javed, H. Larijani, A. Ahmadinia, and D. Gibson, "Smart Random Neural Network Controller for HVAC Using Cloud Computing Technology," IEEE Trans. Ind. Informatics, vol. 13, no. 1, pp. 351–360, 2017.

[26] J. Ahmad, H. Larijani, R. Emmanuel, M. Mannion, A. Javed, and M. Phillipson, "Energy demand prediction through novel random neural network predictor for large non-domestic buildings," 11th Annu. IEEE Int. Syst. Conf. SysCon 2017 - Proc., pp. 1–6, 2017.

[27] A. U. H. Qureshi, H. Larijani, A. Javed, N. Mtetwa, and J. Ahmad, "Intrusion Detection Using Swarm Intelligence," 2019 UK/China Emerg. Technol. UCET 2019, pp. 1–5, 2019.

[28] A. U. H. Qureshi, H. Larijani, J. Ahmad, and N. Mtetwa, "A Novel Random Neural Network Based Approach for Intrusion Detection Systems," 2018 10th Comput. Sci. Electron. Eng. Conf. CEEC 2018 - Proc., pp. 50–55, 2019.

[29] A. U. H. Qureshi, H. Larijani, N. Mtetwa, A. Javed, and J. Ahmad, "RNN-ABC: A new swarm optimization based technique for anomaly detection," Computers, vol. 8, no. 3, 2019.

[30] E.Gelenbe, "Random Neural Networks with Negative and Positive Signal and Product Form Solution."

[31] A. J. Wixted, P. Kinnaird, H. Larijani, A. Tait, A. Ahmadinia, and N. Strachan, "Evaluation of LoRa and LoRaWAN for wireless sensor networks," Proc. IEEE Sensors, vol. 0, pp. 5–7, 2017.

[32] G. G. Anagnostopoulos and A. Kalousis, "A Reproducible Comparison of RSSI Fingerprinting Localization Methods Using LoRaWAN," 2019.

[33] J. N. Purohit and X. Wang, "LoRa based Localization using Deep Learning Techniques," p. 2019, "California State University", 2019.

[34] T. A. Nguyen, "LoRa Localisation in Cities with Neural Networks," p. 71,"Delft University of Technology", 2019.

[35] K. Simonyan and A. Zisserman, “Very deep convolutional networks for large-scale image recognition,” 3rd Int. Conf. Learn. Represent. ICLR 2015 - Conf. Track Proc., pp. 1–14, 2015.