RSS-based Locating in Wireless Sensor Networks using Artificial Neural Network

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Summary
Wireless Sensor Networks are emerging in various domains. One of the most important and challenging services in demand is locating of network nodes. In this paper, we adopted the methodology of the feed-forward neural network. We used the received signal strength of anchor nodes to locate. We also address the dependency of accuracy on the number of anchors and the network configuration. We then evaluate different training algorithms to obtain the best result using the selected training algorithm. Our proposed model is implemented on ESP8266 module for a real-time evaluation of the model performances. An average error of location of 0.189 meter is achieved using four anchor nodes and a neural network structure of 10-10-3. We can also implement this presented method on any embedded locating system.

Key words:
Locating, Neural Network, Wireless Sensor Network, Received Signal Strength (RSS), Real-time

1. Introduction

Wireless Sensor Networks (WSNs) have come under the spotlight in recent years and have been adopted in various domains such as environmental, rescue operation [1], tracking of assets and people in hospitals or in military applications [2] and precise-based tracking of objects in warehouses and targeted advertising [3]. The sensor nodes of WSN are low-cost, small and have low-power consumption and offer interesting data storage, wireless communication, sensing and computing capacities.

The most important service of WSN application is locating (process of the position determination [4]) among other challenging parts such as network architecture, synchronization, security, service quality and nodes' deployment and calibration. For a significant locating, it is required to attach measured data to sensor data. For example, a hospital monitoring would automatically require locations of the medical staff or the person from which information data is received as every medical information has different specific requirements. To manage the application, it is necessary to provide node locations to assist network routing and coverage [5]. Over last years, researchers have addressed the node locating issue by providing various solutions (for example [6], [7], [8], [9], [10], [11], [12], [13], [14]). Usually, there is a trade-off between the complexity of computing, the locating accuracy [15] and the energy consumption. The existing indoor positioning systems achieve good accuracies using measurements from the surrounding locating environment such as Received Signal Strength (RSS), Time Of Arrival (TOA), Angle of Arrival (AOA) and Channel State Information (CSI) [3]. Various techniques are applied on these collected measurements to estimate the mobile node position including lateration [16], dead reckoning [17] and fingerprinting [18]. Fingerprinting is one of the most used indoor locating techniques. In the offline phase, the positioning system builds a database of collected measurements from the locating references in the target location. Then, in the online phase, the system locates in real-time by comparing the new collected measurements to the ones stored in the database. Many indoor positioning systems exploit RSS Wi-Fi values (collected from Wi-Fi locating nodes) due to their low hardware requirements and their simplicity [19] while other systems use CSI data to determine the target node position [20], [21]. Unlike RSS technique, CSI requires the modification of the device driver to adapt the system to Wi-Fi network interface cards.

Multiple machine learning methods are utilized with RSS-based fingerprinting locating to build locating models such as Neural Network [22], Support Vector Machine [23] and k-Nearest Neighbors (KNN) [24]. However, while deep learning is widely used in various domains and showed great results compared to traditional methods, it suffers from limitation on its ability to fully exploit the training data to learn the feature complexity. Thus, recent works on RSS-based indoor locating system [25],[26],[27],[28] explored deep learning models and used them to determine the target node position.

WSN usually has a large spatial distribution of nodes which make the locating process very difficult when the nodes of the network are deployed. It may also be possible to move a node in different location within the network. For this purpose, it is required to implement an autonomous algorithm for the determination of locations. In this work, we propose a neural network-based locating in a wireless sensor network. We used the received Signal Strength (RSS) to determine locations of wireless sensor nodes. We made the following contributions:

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- We used RSS values to determine locations of sensor nodes and explain their suitability for locating. No extra hardware will be required as the ESP8266 nodes are equipped with radio frequency modules for wireless communication. However, collected RSS values are affected by noise and multipath fading.
- We considered a 2-D indoor locating environment, that are x and y coordinates to define locations. Thus, the ESP8266 module has a PCB antenna (which is not exactly omni-directional) that allows almost equal performances regardless of the module orientation and heading. We explained the best configuration of anchor nodes used in our experiment.

We present a 2-D indoor locating based on neural network. Global Positioning System (GPS) [29] is generally used for accurate locating. However, it cannot be employed in indoor environment due to required Line-Of-Sight signal when locating. Our method uses a feed-forward artificial neural network. We trained the network structures using Bayesian Regularization (BR), Levenberg Marquardt (LM), Scaled Conjugate Gradient (SCG), Gradient Decent (GD), Resilient Back-propagation (RP) and evaluate it to employ the bet neural network.

2. The proposed neural network based mothed

2.1 Definition of the locating problem

Let us consider the deployment of n number of sensor nodes N= {N1, N2, … , Nn} with their respective locations L={L1,L2,… ,Ln}. Lxj, Lyj, Lzj are respectively the x, y and z coordinates of jth sensor node. With Lzj=0, we obtain a 2-D locating. The network nodes locate themselves using anchor nodes and every sensor node has knowledge of its location as anchor nodes. Thus, the node locating problem can mathematically be states as follows:
For a given WSN represented by a W= (V, E) with M anchor nodes having positions {xm, ym} for all m $\in$ M, we determine the coordinates {xk, yk} for nodes with unknown positions k $\in$ K.

2.2 Methodology

Artificial Neural Network or Neural Network is a practical method for discrete and real values functions learning. We can obtain supervised learning with the use of ANN. We provide Inputs and outputs for the neural network to learn and create a suitable model. We generally use the ANN for regression and classification. A multiplayer neural network usually has interconnected neurons in three layers: input layer, hidden layers and output layer.

There are two types of neural network:

- **Feed-forward**: there is no feedback to the system and the outputs feed the next layer of the neural network.
- **Feedback**: there are feedbacks to the system and the inputs/outputs feed the next layer of the neural network.

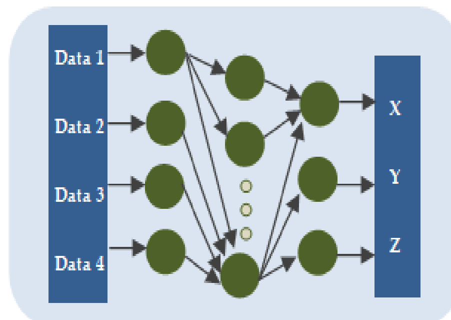

Fig. 1 Structure of a general feed-forward Neural Network with 5 inputs and 3 outputs

The main three neural network types used for locating [30] are Recurrent Neural Network (RNN), MLP and radial Basic Function (RBF).
Collected RSS values are very unstable and can easily be affected by the sensor node mobility and noise within the environment. By using the neural network, the knowledge of noise distribution and the environment becomes unnecessary. Thus, unlike other techniques (Kalman filter …) we can obtain higher locating accuracies by using the neural network.
By comparing the three neural network types, MLP offers the best trade-off between requirements of the memory and accuracy. MLP comes as the best one. Therefore, we used it in this study.
We used Matlab for MLP neural network implementation (feed-forward artificial neural network). We adopted the solution shown in Figure 1 with three inputs, three nodes in the output layer, and ten nodes in both the first and the second layers. We use the collected RSS from three anchor nodes as inputs of the neural network to obtain the mobile node coordinates (x, y) in the output.
In the first and the second layer, the nodes use the activation function of hyperbolic tangent sigmoid. The third layer use “purelin” as a linear activation function. We adopted the Bayesian Regularization algorithm (BR)

as the training algorithm of our system because it gives optimal results. As the BR algorithm is only required in offline phase, we employed it although its training time was high. The output coordinates and RSS values in the matrix structure are as shown in (1).

$$data = \begin{bmatrix} rss11 & rss12 & rss1i & x1 & y1 \\ rss21 & rss22 & rss2i & x2 & y2 \\ \dots & \dots & \dots & \dots & \dots \\ rssij1 & rssij2 & rssji & xi & yi \end{bmatrix} \quad (1)$$

Where:

- $\mathbf{rss_{ij}}$ are the values of **rss** signals at the $\mathbf{i^{th}}$ node (reference point), from the $\mathbf{j^{th}}$ anchor node.
- **xi** and **yi** are the coordinates of the $\mathbf{i^{th}}$ anchor (reference point).

For this study, we used three anchor nodes and a total number of nodes (reference nodes) of ten.
Our obtained neural network is as shown in equation (2).

$$\begin{bmatrix} x \\ y \end{bmatrix} = \tanh(\tanh(rss * w1i + b1i) * w2j + b2j) * w3m) + b3m \quad (2)$$

Where:

- **rss** are the values of **rss** signals collected from three anchor nodes (row vector of length three).
- $\mathbf{w_{nm}}$ is the mth node at the nth layer weight vector.
- $\mathbf{b_{nm}}$ is the bias vector the mth node at the nth layer.

We incorporated equation (2) on a mobile node based on ESP8266 module for node locating. It can also b implemented on other platform of programming.

3. Data Collection

3.1 RSS values collection

For the experiment, we used ESP8266 modules which are compliant with the IEEE 802.11n standard called Wi-Fi as sensor nodes. Anchor nodes are constituted using ESP8266 modules. The node communicates by the standard Wi-Fi communication that serve data at over 7Mbps and operate at 2.4 GHz frequency band which is the ISM band (Industrial, Scientific and Medical). The ESP8266 transmitter has a transmitting power of +14Bm that is 25mW (TX power of IEEE 802.11n transmitter), the ESP8266 receiver sensibility is -72dBm that is 6 to the power of -8 mW and a communication range of about 20-40 meters for indoor environments. The ESP8266 module has the RSSI().Signal() feature which permit to read RSS values.
Anchor nodes receive a signal from mobile nodes as a request to send locating data. Anchor node then sends locating data to mobiles nodes. The mobile node receives one RSS value from anchors nodes (Figure 2). We collect RSS values using Arduino software and analyze it using Matlab software running on Windows 8.1.

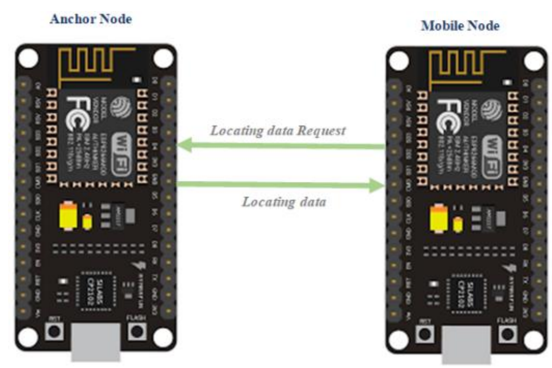

Fig. 2 Communication between anchor node and mobile for RSS measurements

3.2 RSS values collection

The neural network training and testing phases require a set of data [28]. In this study, we created the dataset using the collected RSS for each mobile node. Experimental environment structure is very important for indoor locating [31]. Collection of RSS is carried out in indoor location that contains tables, computers and chairs. As shown in Fig. 3., the collected training data structure is 5x6 measurements points (red points). Distance between grid points is 0.2 meter. We used measurements of the training positions and the unknown positions for testing. As illustrated in Fig. 3., we chose the unknown positions (blue points) between the points of the training measurements.
In order to determine the best nodes configuration for our application, we used the following configurations:

- 2 anchors: 1 and 3, 2 and 3.
- 3 anchors: 1, 2 and 3, 1, 3 and 4.
- 4 anchors.

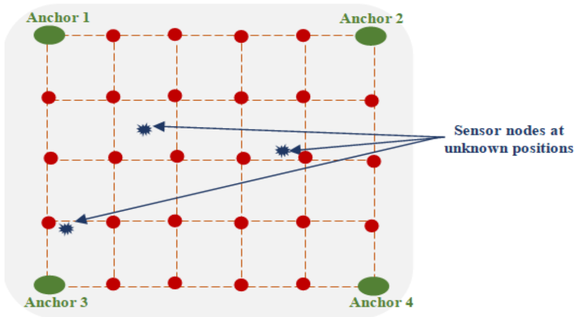

Fig. 3 Setup layout of the experiment

4. Results

For this study, we used five training algorithms (LM, RP, GD, BR, and SCG) as the neural network requires a supervised learning. We conducted tests with varying the number of nodes, the layers and the various activation functions. Optimal results were obtained using a three-layer network with 12-2-2 structure. We employed:

- Ten nodes in the first and second layers (hidden).
- Three nodes in the output layer.

And we used:

- The function of the output layer is "Pureline".
- The activation function is "hyperbolic-tangent sigmoid".

In order to evaluate the performance of the configuration of different anchor nodes, we use the 10-10-3 structure with different number of nodes as inputs.
To obtain the best training algorithm for our neural network, we perform the experiment using four anchors. The data structure we used for training consists of 3000 data sets (70 percent used for training and validation, 30 percent used for the test). Furthermore, we tested the performance of the network using 100 data sets (obtained from two unknown positions). We evaluate the network performance by comparing the estimated distance to the exact distance. Equation 3 illustrates the average error between both estimated and exact distance:

$$error = \sum_{i=1}^{n} \frac{1}{n}\sqrt{(xe - xi)^2 + (ye - yi)^2} \qquad (3)$$

Where:

- n is the number of data sets used for the test.
- (xe, ye) is the estimated position of the mobile node at the ith data sets of the tests.
- (xi, yi) is the estimated position of the mobile node at the ith data sets of the tests.

Average locating error obtained in the test phase is shown in table 1 and the training time using the five training algorithms is illustrated in table 2.

Table 1: Location error of different algorithm using 4 anchor nodes

Locating algorithm	GD	SGC	RP	BR	LM
Average Error (m)	0.78	0.51	0.47	0.08	0.12
Maximum Error (m)	2.35	2.24	2.13	1.28	1.43
Average error (m) at an unknown location	1.14	0.78	0.67	0.36	1.79

Table 2: training time of the neural network for different algorithm using 4 anchor nodes

Locating algorithm	GD	SGC	RP	BR	LM
Training time	823 s	83 s	186 s	725 s	67s

We obtained an average error percentage less than 0.75 meter. GD, SCG and RP algorithms have low errors while they have a quite high maximum error compared to BR and LM training algorithms. Training time of GD and BR algorithm is also high compared to the other three algorithms. Thus, in our case we chose BR and LM algorithms because the training of the neural network is performed in offline. Those algorithms are used for the neural network that will be implemented on the mobile node.

The locating error for different anchor node configurations (LM and BR training algorithm) of the neural network is shown in table 3 and 4. We obtained the lowest average errors of those configurations using four nodes network. Maximum error of LM algorithm is quite the same when using three and four anchor nodes. The configuration with anchors 1, 3 and 4 gives slightly better results compared to configuration with anchors 1, 2 and 3.

Table 3: Average and Maximum error for BR and LM algorithms using different configurations of anchors

Anchor Nodes	**1 and 3**		**2 and 3**		**1,2 and 3**		**1,3 and 4**		**1,2,3 and 4**	
Locating algorithm	BR	LM	BR	LM	BR	LM	BR	LM	BR	LM
Average error (m)	0.5	0.52	0.45	0.48	0.22	0.31	0.28	0.23	1.17	0.189
Maximum error (m)	3.1	2.37	2.72	2.62	2.83	2.12	2.02	2.25	1	2.26

Table 4: LM algorithm average errors at an unknown position for different configurations of anchors

Anchor Nodes	**1 and 3**	**2 and 3**	**1,2 and 3**	**1,3 and 4**	**1,2,3 and 4**
Average Error (m) at an unknown location	1.14	1.38	1.22	1.19	0.87

Results show that when the required locating accuracy is less than few meters, RSS-based locating can be used. However, we can add sensors (ultrasonic [14] …) for RSS-based locating applications to increase the accuracy.

Author in [32] presented a 2-D/3-D locating algorithm using the technique of Weighted Centroid (WCL) which controls the involved anchor nodes by an optimized threshold. Author in [33] used a modified high-resolution range-independent (HIRLoc) locating technique using omni-directional antennas. A comparison between our proposed technique and those presented below is given in the table below. Neural network for 3-D locating with four anchor nodes [34] has an average error of 0.4855 meter for 2-D locating. In our study, we achieved a locating error less than 0.75 meter of 97% of the mobile nodes. We used a 10-10-3 structure for our neural network with four inputs. The first layer uses the hyperbolic tangent sigmoid as an activation function while the second layer use the log sigmoid as the activation function and the output uses a linear function as an activation function. We then obtained an average locating error of 0.189 meter using four anchors which is lower than result in [34]. Thus, our proposed algorithm is carried out in a real indoor environment whereas the algorithm in [34] is based on simulation.

Table 5: Comparison of locating algorithms and our proposed method

Locating algorithm	Environment	Anchor number	Average error
WCL(2-D) [32]	Simulation	100	> 3 meters
Modified HIRLoc Scheme [33]	Simulation	-	3.51 meters
Neural Network [34]	Simulation	4	0.4855 meter
Our proposed technique	Real-time	2	0.547 meter
		3	0.235 meter
		4	meter

5. Conclusion

In this paper, we proposed an efficient 2-D locating algorithm for WSN based on the artificial neural network. Depending on our application environment and by selecting the number of anchor nodes, we studied the performances of various anchor configurations. Using collected RSS values , we evaluated five training algorithms (LM, RP, GD, BR, and SCG) to obtain the best neural network structure. BR algorithm showed the best result but with a quite high training time compared to the other algorithms. For this, the BR algorithm can be used for application wherein the training phase is offline while the LM algorithm can be used for application wherein the training is online.

By using the two messages communication protocol to obtain the locating inputs, our proposed sytem manages energy and resources efficiently.

For future works, our works will aim to find the best filtering method of RSS values received by anchor nodes and the best network topology to reduce the locating error.

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References

[1] França, Reinaldo Padilha, “Intelligent Applications of WSN in the World: A Technological and Literary Background”, Handbook of Wireless Sensor Networks: Issues and Challenges in Current Scenario's. Springer, Cham, 2020. 13-34.

[2] Akyildiz, Ian F., Su, Weilian, Sankarasubramaniam, Yogesh, al., “Wireless sensor networks: a survey”, Computer networks, 2002, vol. 38, no 4, pp. 393-422.

[3] F. Zafari et al., “A Survey of Indoor Localization Systems and Technologies,” ArXiv preprint, 2017.
[4] Pohudina, Olha, et al. “Possibilities of Position Determination”, Integrated Computer Technologies in Mechanical Engineering, Springer, Cham, 2020. pp. 523-537.
[5] Pal, Amitangshu., “Localization algorithms in wireless sensor networks: Current approaches and future challenges”, Network Protocols & Algorithms, 2010, vol. 2, no 1, pp. 45-73.
[6] Velimirović, Andrija S., Đorđević, Goran Lj, Velimirović, Maja M., al., “A fuzzy set-based approach to range-free localization in wireless sensor networks”, Facta universitatis-series: Electronics and Energetics, 2010, vol. 23, no 2, pp. 227-244.
[7] Di Stefano, Gabriele et Petricola, Alberto, “A Distributed AOA Based Localization Algorithm for Wireless Sensor Networks”, JCP, 2008, vol. 3, no 4, pp. 1-8.
[8] Jiang, Jehn-Ruey, Lin, Chih-Ming, Lin, Feng-Yi, “ALRD: AoA localization with RSSI differences of directional antennas for wireless sensor networks”, International Journal of Distributed Sensor Networks, 2013, vol. 9, no 3, pp. 489- 529.
[9] Xing, Jianping, Wang, Dehua, et Liu, Yang., “Distributed range-free localization algorithm for 3d wireless sensor networks under irregular radio propagation model”, International Conference on Applied Informatics and Communication. Springer, Berlin, Heidelberg, 2011. pp. 299-306.
[10] Abdelhadi, M., Anan, M., et Ayyash, “M. Efficient artificial intelligent-based localization algorithm for wireless sensor networks”, Cyber Journals: Multidisciplinary Journals in Science and Technology, Journal of Selected Areas in Telecommunications (JSAT), 2013, vol. 3, pp. 10-18.
[11] BULUSU, Nirupama, HEIDEMANN, John, et ESTRIN, Deborah. GPS-less low-cost outdoor localization for very small devices. IEEE personal communications, 2000, vol. 7, no 5, pp. 28-34.
[12] OGUEJIOFOR, O. S., ANIEDU, A. N., EJIOFOR, H. C., et al.Trilateration based localization algorithm for wireless sensor network. International Journal of Science and Modern Engineering (IJISME), 2013, vol. 1, no 10, pp. 2319-6386.
[13] TANG, Tao, GUO, Qing, et PENG, Bao. Sorted TDOA optimization based localization algorithm for wireless sensor network. Computer Engineering and Applications, 2008, vol. 44, no 25, pp. 98-99
[14] CHARLON, Yoann, FOURTY, Nicolas, et CAMPO, Eric. A telemetry system embedded in clothes for indoor localization and elderly health monitoring, Sensors, 2013, vol. 13, no 9, pp. 11728-11749
[15] CHENG, Bo, DU, Rong, YANG, Bo, et al. An accurate GPS-based localization in wireless sensor networks: A GM-WLS method. Proceeding of the 40th International Conference on Parallel Processing Workshops. IEEE, 2011. p. 33-41.
[16] J. Yang and Y. Chen, ”Indoor Localization Using Improved RSS-Based Lateration Methods,” IEEE GlobeCom, Honolulu, HI, 2009, pp. 1-6.
[17] M. Alzantot and M. Youssef, ”UPTIME: Ubiquitous pedestrian tracking using mobile phones,” IEEE WCNC, Shanghai, 2012, pp. 3204-3209.
[18] S. He et al., ”Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons,” in IEEE Commun. Surveys Tuts., 2016, Firstquarter, vol. 18, no. 1, pp. 466-490.
[19] W. Njima et al., “Smart probabilistic approach with RSSI fingerprinting for indoor localization,” SoftCOM, Split, 2017, pp. 1-6.
[20] X. Wang et al., ”CSI Phase Fingerprinting for Indoor Localization With a Deep Learning Approach,” in IEEE IoT-J, vol. 3, no. 6, pp. 1113-1123, Dec. 2016.
[21] H. Chen, Y. Zhang et al., “ConFi: Convolutional Neural Networks Based Indoor Wi-Fi Localization Using Channel State Information”, in IEEE Access, vol. 5, pp. 18066-18074, 2017.
[22] S. Dayekh et al., ”Cooperative Localization in Mines Using Fingerprinting and Neural Networks,” IEEE WCNC, Sydney, NSW, 2010, pp. 1-6.
[23] H. Liu et al., ”Survey of Wireless Indoor Positioning Techniques and Systems,” in IEEE Trans. Syst., Man, Cybern. fCg, vol. 37, no. 6, pp. 1067-1080, Nov. 2007.
[24] W. Zhang et al., ”Deep neural networks for wireless localization in indoor and outdoor environments”, Neurocomputing, vol. 194, pp. 279- 287, Jun. 2016.
[25] G. Flix et al., ”A fingerprinting indoor localization algorithm based deep learning,” ICUFN, Vienna, 2016, pp. 1006-1011.
[26] M. Nowicki and J. Wietrzykowski, ”Low-Effort Place Recognition with WiFi Fingerprints Using Deep Learning”, in Szewczyk R., Zieliski C., Kaliczyska M. (eds) ICA 2017. Advances in Intelligent Systems and Computing, vol 550. Springer, Cham
[27] K. S. Kim et al., ”A Scalable Deep Neural Network Architecture for Multi-Building and Multi-Floor Indoor Localization Based on Wi-Fi Fingerprinting,” ArXiv preprint, 2017.
[28] Shareef, Ali, Yifeng Zhu, and Mohamad Musavi. “Localization using neural networks in wireless sensor networks”, 1st international conference on MOBILe Wireless MiddleWARE, Operating Systems, and Applications, ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2008.
[29] “Types of wireless communication protocols”, 25 February 2020. [interactive]. Available : https://iotdesignpro.com/articles/different-types-of-wireless-communication-protocols-for-iot
[30] Fang, Shih-Hau et Lin, Tsung-Nan. Indoor location system based on discriminant-adaptive neural network in IEEE 802.11 environments. IEEE Transactions on Neural networks, 2008, vol. 19, no 11, pp. 1973-1978.
[31] Pletl, Silvester, et al. “Optimizing coverage in mobile wireless sensor networks”, IEEE 8th International Symposium on Intelligent Systems and Informatics. IEEE, 2010.
[32] Xu, L., Wang, K., Jiang, Y., Yang, F., Du, Y., & Li, Q. “A study on 2D and 3D weighted centroid localization algorithm in wireless sensor networks”, Proceeding of the

3rd International Conference on Advanced Computer Control. IEEE, 2011, pp. 155-159.
[33] Dubey, Tarun et Sahu, O. P. “Directional antenna assisted scheme to reduce localization error in wireless sensor networks”, International Journal of Information and Network Security, 2013, vol. 2, no 2, p. 183.
[34] Abdelhadi, M., Anan, M., et Ayyash, M. Efficient artificial intelligent-based localization algorithm for wireless sensor networks. Cyber Journals: Multidisciplinary Journals in Science and Technology, Journal of Selected Areas in Telecommunications (JSAT), 2013, vol. 3, pp. 10-18