ISSN(Online): 2320-9801
ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(A High Impact Factor, Monthly, Peer Reviewed Journal)

Website: www.ijircce.com

Vol. 6, Issue 10, October 2018

Investigation of Wireless Sensor Network Node Localization with Reduced Power Consumption

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ABSTRACT: Wireless sensor networks are a type of wireless network that contains wireless sensors and are used in many fields. Sensors in this type of network are small, low cost, consume a small amount of energy and able to communicate with each other over a short distance. These networks are composed of a large number of sensors, which are usually deployed in random different places. As these networks may be fixed in a dangerous area or difficult to reach, such as a battlefield or around a volcanic eruption.

The process of determining the real geographical location of these sensors is called localization and the location is very important as in most applications in this field, the data received without knowing its location is useless. There are several methods used to determine the geographical location of the sensor from which the data was received, including the global positioning system (GPS). However, in this type of networks, sensors are deployed in large numbers, which requires providing these large numbers of sensors with the positioning system for each sensor. Adding this technique to the sensors increases their physical cost. In addition, the GPS system needs a lot of energy when used. This reduces the life of the default sensor battery, thereby reducing the accuracy of the GPS system and it becomes difficult to obtain information about the location in the closed area.

Because the sensors' location cannot be exactly determined, they are usually distributed randomly (also new sensors may be added to the network or the energy of some sensors may depleted causing their exit from the network). This paper focuses on the use of artificial neural networks (ANNs) to determine the geographical location of wireless sensor networks depending only on three known location nodes (anchor nodes) located in different locations. The results are compared in order to obtain the coordinates of all wireless sensors to be deployed or to be added in future, taking into consideration the use of reduced power needed for the purpose of sending and receiving the information on the location.

KEYWORDS: Wireless Sensor Network, Back Propagation Algorithm, Neural Network, Levenberg-Marquardt, Anchor Nodes, Artificial Neural Network, Zigbee.

I. INTRODUCTION

In recent years, information technology has become a major part of our life. The ability of advanced computers to perform complex operations, as well as advances in both computer networks and embedded systems, has affected many aspects of human life. High-resolution, computer-related cameras are now used in many security applications, For example, it is used to monitor important establishments and airports as well as follow traffic [1].

Several experimental models have been designed to demonstrate the feasibility of deploying a large number of sensors in a limited area, where they cooperate in the formation of a wireless network to monitor the phenomenon under study. These equipment are deployed according to a specific scenario of localizations to spread the devices which can be determined in advance. In the case of random spreading, sensors are usually deployed by helicopters. In both sensors, It is important in the field to study the broadcast data and the energy that should be supplied to the main station to make it available to the user.

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For wireless networks be able to perform effectively, there are many challenges to be faced. These include limited power, low memory and medium computing capacity. The ability to deploy, guide, integrate data and process information are the most existing challenges facing the network growth.

II. Related work

WSN localization is an active area of research with several surveys [1] - [5], on this topic. In 2008, K. Benkic, et al.[2] indicated that for WSNs -indoor type, RSSI is a low accurate distance estimator. Many factors such as reflection, scattering and other physical characteristics have an extreme influence on RSSI measurements. As a conclusion, they stated that RSSI is a bad distance estimator. In 2013, Shikhabhardwaj [1] examine the use of ANNs as a method of localization in WSNs. To solve for the localization process, a back propagation algorithm (BPN) was used in the training phase based on multi-layer perceptron (MLP) neural networks. In the test phase, a new independent set of data was tested to prove the effectiveness of proposed neural network. The analysis covered other variables like number of anchor nodes, hidden layers-neurons, etc. which had impacts on the efficiency of the neural network. Localization mechanisms (which is not based on GPS) were studied in 2015, by Alkubeily [3] while applying them in WSN. The effectiveness of using MUSIC algorithm was tested for the determination of the angle of signal arrival depending on the SDMA- technology and ESPAR antenna.

In 2017, Mohsin [4] proposed a refining method to get a precise estimation of the distance between sensor nodes. In self localization, different factors affecting the measurements of round trip time (RTT) values were studied. The discussion of the results of two estimating distance methods was given with their simulations and evaluations. A considerable improvement in determining a near-exact localization was achieved. In 2018, an improvement in the lifetime of a randomly deployed network was achieved by, Talib [5], by scheduling the impacts of transmission, reception and sleep states on the energy consumption of the sensor node. Studying and discussion of the results of the above mentioned states were also given with many performance.

III. Proposed Methodology And Discussion

The purpose of the localization technique is to determine the location of the real or relative geo-sensor. Usually, the location is used by sensors within the wireless network called the anchor node. These wireless sensors are either equipped with GPS or The coordinates are given programmatically before being placed in the network and adopted as a reference point to find out the exact locations of the rest of the wireless sensors. There are three different stages in the localization process, as shown in Figure (1). They are the estimation of the distance or angle between the nodes, the calculation of one location and a localization algorithm-used for localization of whole network.

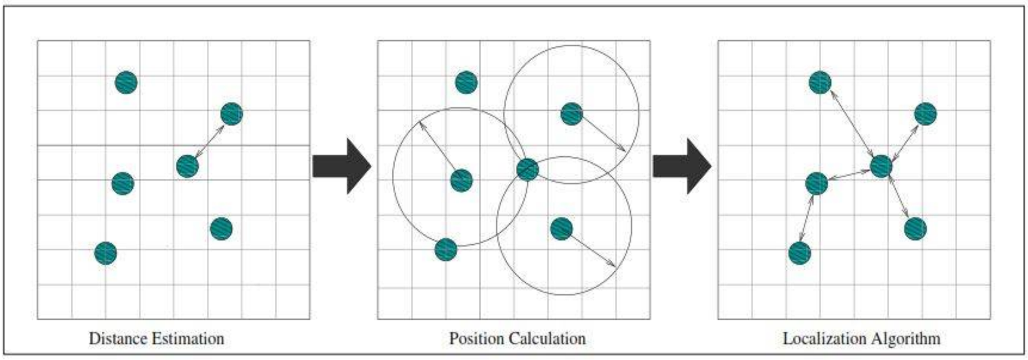

Figure (1) Three-stage localization.

There are several techniques and methods of calculation at each stage. They are described in the next paragraphs:

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A- Estimating the distance or angle between nodes.

Here, the distance or angle between sending and receiving nodes is estimated. That is the initial stage of the next two stages of the localization process. There are several techniques for determining distance and angle between nodes. One of these techniques is Time of Arrival (TOA). This technique exists in GPS and depends on the transmission time of a radio frequency (RF) signal from the sender to the recipient where the arrival time can be calculated. Another technique is the Time Difference of Arrival (TDOA) which is a developed from TOA [6]. The node sends two different signals (radio and sound) to its neighbors. The distance is then calculated depending on the difference in time of propagation of both radio and sound signals from starting the same point and the speed of each signal. The receiving node calculates the difference between arrival times of both signals from which the distance can be obtained. Another technique is the Received Signal Strength Indication (RSSI). It is well known that a radio signal strength decreases exponentially as the distance between the transmitter and receiver increases. The attenuation in signal strength is measured by the RSSI circuit. RSSI estimates the distance covered by a signal to the receiver by measuring the power of received signal. Any decrease in the transmitted power at the receiver is well sensed and translated into an estimated distance [7]. Angle of arrival (AOA) is also a technique uses the direction of each reference node with respect the sensor node to calculate the location of the unknown nodes, where the angle at which the signal is received is used as a reference to estimate the distance of the sent node using simple geometric relationships. AOA is measured using a directional antenna or antenna arrays.

B- Position calculation

This techniques is used to estimate the node's location based on anchor nodes which are positioned some geometric technique; such as trilateration and triangulation. Trilateration is a geometric technique used to locate an unknown node based on the location of three or more anchor nodes. To calculate the position, the distance between the anchor nodes and the unknown node is used. Another geometric technique is triangulation that uses the trigonometry laws of sine and cosines on the angles of the incoming signal to estimate the location of the sensor sending to the signal. The angle of arrival measurement by this method needs a large, expensive hardware (e.g. multi-sectored antenna) that is not suitable to fix in small wireless sensors.

C- Localization algorithm

Localization algorithms are the last and most important stage in the localization system. They invest information from the previous two stages and explain how this information is transmitted to obtain sensors locations. Localization algorithms can be divided according to transferring information into:

i. Centric: In this algorithm, location information is transferred from all the sensors in the network to an efficient central node.

ii. Multiplexer: Here, the location information is calculated for each wireless sensor itself and communicates with the other sensors in order to determine the location of the remaining sensors within the network [8].

On the other hand, location algorithms are divided according to the ranging into:

i. Range-based algorithms: The received information from the beacon node is used here to identify the location of the unknown node [9]. There are several algorithms based on the range principle such as (TOA [10], TDOA [6], AOA [6], and RSSI [7]). Range-based algorithms give higher accuracy information with more cost of hardware and more power consumption.

ii. Range free algorithms: these algorithms depend on the contact information between the unknown node and the landmark nodes. These landmarks are either equipped with a GPS or placed in a location with known coordinates. The range free algorithms have lower hardware costs, lower energy consumption, and more efficient in localization. Centroid[11] and DV-HOP[12] are examples of range free algorithms. In the Centroid algorithm, the position is calculated by number of beacon signals received from the previously positioned beacon node. Whereas, DV-HOP algorithm uses the location of the beacon node, the number of hops from the beacons and the average distance for each hop to calculate the location.

In this paper, 100 wireless sensor nodes are randomly deployed over a geographical area of (100m x 100m) meters in addition to the deployment of 3 anchor nodes in eight different known locations. A Matlab(2018a) program is used for this purpose. The distances between the anchor nodes and these random nodes are calculated theoretically using Euclidian distances. Such distances are then used as inputs for an ANN that is trained to find the exact location of the

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nodes. The results obtained in each case of distribution of the anchor node on the geographical area are compared, to reach the best location in terms of the proportion of error in reading. In practice, the received signal strength is measured in an outdoor place called Eitet in Duhok, Kurdistan region, Iraq by using two pieces of Xbee s2c models which are programmed, one as a router and the other as a coordinator besides applying the XCTU Software. Figure (2) shows the measured RSSI verses the distance in both operating modes (normal mode and boost mode) of Xbee S2C.

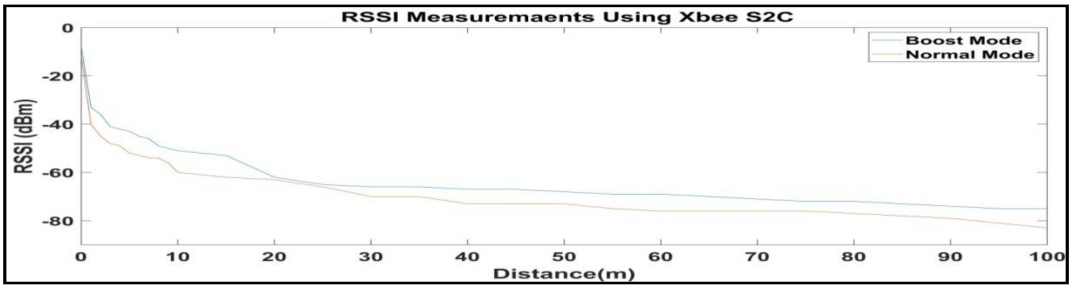

Figure (2) Measured RSSI versus the distance for normal and boost modes.

Since this paper seeks for node localization with reduced power consumption, it is clear from Figure (2) that the normal mode of the Xbee s2c module is the best for that purpose and therefore will be applied throughout all next measurements and calculations. ANNs used in this work are a feed forward network and the training algorithm is of the Levenberg–Marquardt type. First of all, three anchor nodes are placed in 8 different locations for different cases of study. These locations are illustrated through the grid shown in Figure (3) and given as

1. Location (1) at AN1(100,0) AN2(100,100) AN3(0,100) , denoted as (a100).
2. Location (2) at AN1(25,50) AN2 (50,50) AN3 (75,50) , denoted as (a50).
3. Location (3) at AN1(25,25) AN2(50,50) AN3(75,75) , denoted as (b50).
4. Location (4) at AN1(25,75) AN2(50,50) AN3(75,25) , denoted as (c50).
5. Location (5) at AN1(25,25) AN2(50,50) AN3(75,25) , denoted as (d50).
6. Location (6) at AN1(25,75) AN2(50,50) AN3(75,75) , denoted as (e50).
7. Location (7) at AN1(25,34) AN2(50,77.3) AN3(75,34) , denoted as (f50).
8. Location (8) at AN1(27.85,30.82) AN2(50,69.18) AN3(72.15,30.82) , denoted as (g50).

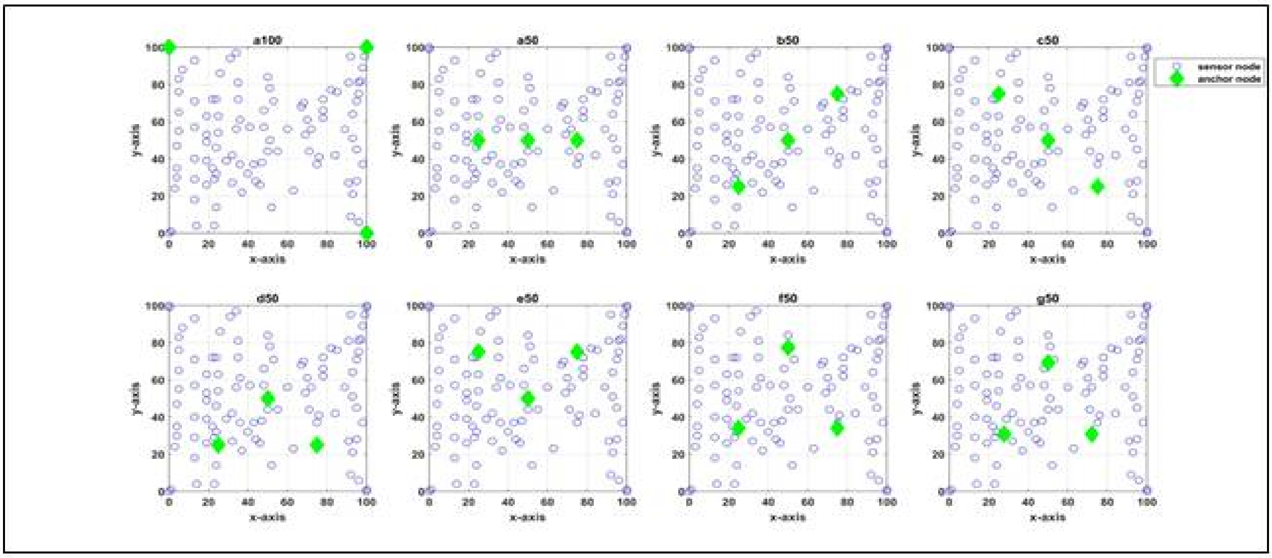

Figure (3) Grid of the network showing sensor nodes and anchor nodes location for 8 cases.

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IV. SIMULATION RESULTS

A source code is implemented using MATLAB R2018a to deploy 100 sensors randomly in (100m x 100m) geographical area. MATLAB R2018a is also used to train the ANNs by using the coordinates of these nodes that have been deployed. The training was carried out by designing the following ten ANNs using the (nntool) tool in the MATLAB program and Levenberg-Marquardt training algorithm. The distances between the sensor node and the anchor node represent the inputs to these neural networks and the outputs are the coordinates of the sensor nodes.

1- Neural network consists of a single layer with a log sigmoid activation function.
2- Neural network consists of a single layer with a tan sigmoid activation function.
3- Neural network consists of 2 layers, with a log sigmoid activation function in the hidden layer containing (1) neuron and a single output layer with a linear activation function.
4- Neural network consists of 2 layers, with a tan sigmoid activation function in the hidden layer containing (1) neuron and a single output layer with a linear activation function.
5- Neural network consists of 2 layers, with a log sigmoid activation function in the hidden layer containing (3) neurons and a single output layer with a linear activation function.
6- Neural network consists of 2 layers, with a tan sigmoid activation function in the hidden layer containing (3) neurons and a single output layer with a linear activation function.
7- Neural network consists of 2 layers, with a log sigmoid activation function in the hidden layer containing (5) neurons and a single output layer with a linear activation function.
8- Neural network consists of 2 layers, with a tan sigmoid activation function in the hidden layer containing (5) neurons and a single output layer with a linear activation function.
9- Neural network consists of 2 layers, with a log sigmoid activation function in the hidden layer containing (10) neurons and a single output layer with a linear activation function.
10- Neural network consists of 2 layers, with a tan sigmoid activation function in the hidden layer containing (10) neurons and a single output layer with a linear activation function.

Comparing the outputs of ANNs with the required outputs, Table (1) can be formed representing the average percentage error in each case.

Table (1) Average errors for each case.

	1 Layer		2 Layers							
Case	log sigmoid	tan sigmoid	1 neuron in hidden log sigmoid	1 neuron in hidden tan sigmoid	3 neurons in hidden log sigmoid	3 neurons in hidden tan sigmoid	5 neurons in hidden log sigmoid	5 neurons in hidden tan sigmoid	10 neurons in hidden log sigmoid	10 neurons in hidden tan sigmoid
a100	0.138752558	0.040565876	0.133347	0.130700	0.003039	0.003193	0.000239	0.001040	0.000017	0.000190
a50	0.193963363	0.147089567	0.142093	0.141339	0.117032	0.123614	0.128444	0.116865	0.125195	0.120513
b50	0.223023359	0.158602057	0.154981	0.155802	0.134866	0.134017	0.137500	0.121790	0.118432	0.116728
c50	0.204381772	0.17811469	0.180818	0.182019	0.167541	0.174761	0.131342	0.149056	0.134558	0.126440
d50	0.140540993	0.064954338	0.147909	0.142296	0.038020	0.004036	0.001883	0.000214	0.001468	0.001266
e50	0.147127234	0.06907905	0.149688	0.141579	0.004272	0.039568	0.002155	0.002223	0.000295	0.000405
f50	0.144205367	0.070093779	0.151034	0.070094	0.003883	0.003907	0.005300	0.000358	0.000030	0.000017
g50	0.14257643	0.06984847	0.149689	0.145147	0.003839	0.003692	0.004442	0.000225	0.000012	0.000019

Figures (4)-(6) represent a comparative analytic values of the maximum, minimum and average percentage errors related to the above mentioned cases. From these figures, it can be seen that the minimum and average errors take the

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most reduced values in the neural network consisting of 2 hidden layers and (10) neurons, with a tan sigmoid activation function and a single output layer with a linear activation function.

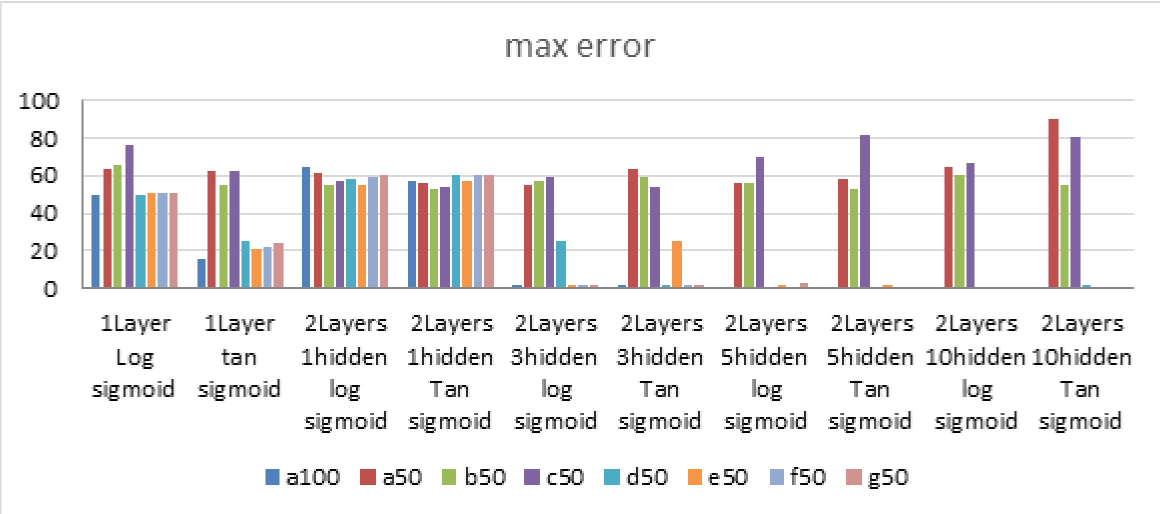

Figure (4) Maximum percentage errors in the 10 ANNs for the 8 cases.

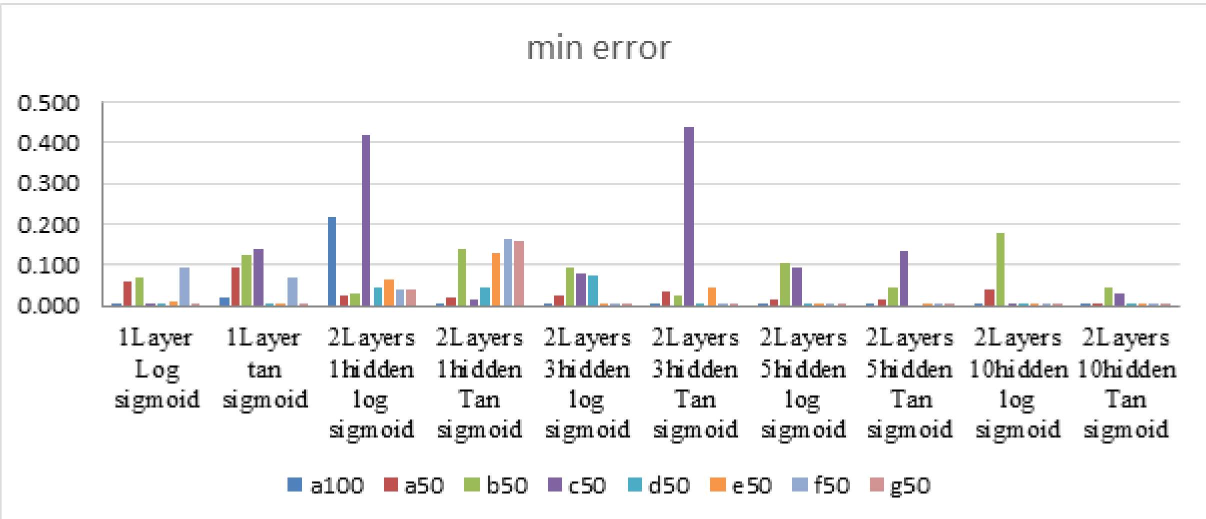

Figure (5) Minimum percentage errors in the 10 ANNs for the 8 cases.

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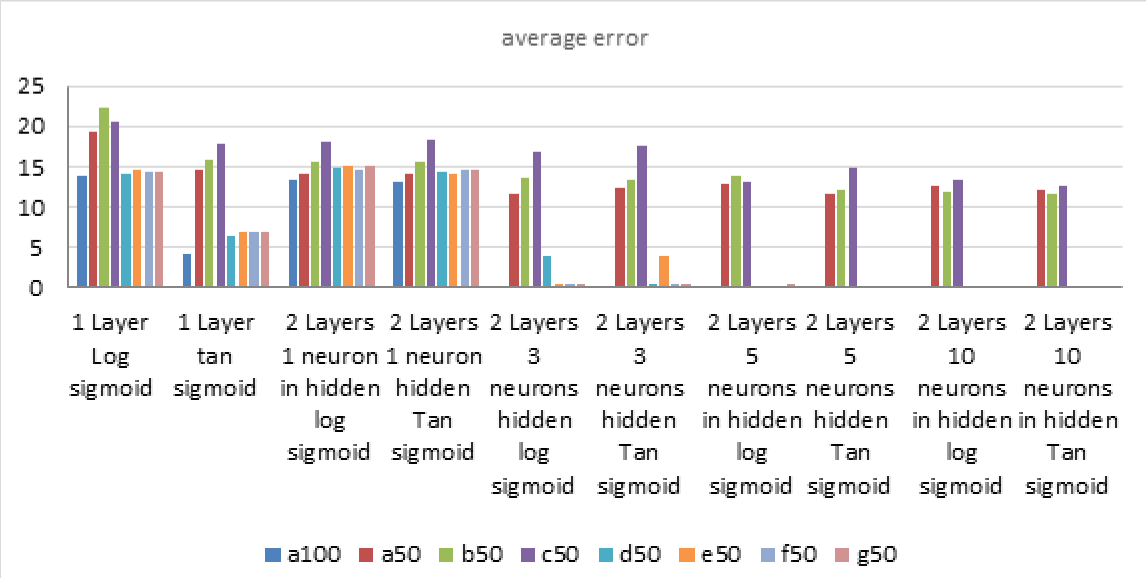

Figure (6) Average percentage errors in the 10 ANNs for the 8 cases.

The trained networks are then tested for the locations of five nodes that are randomly deployed on the (100m x 100m) grid. The results obtained through the 8 cases of anchors nodes locations are compared and the ANNs that are designed. For e.g. , Figure (7) shows the real locations of five nodes obtained using ANNs that are previously trained; based on three anchor nodes which are deployed by case e50.

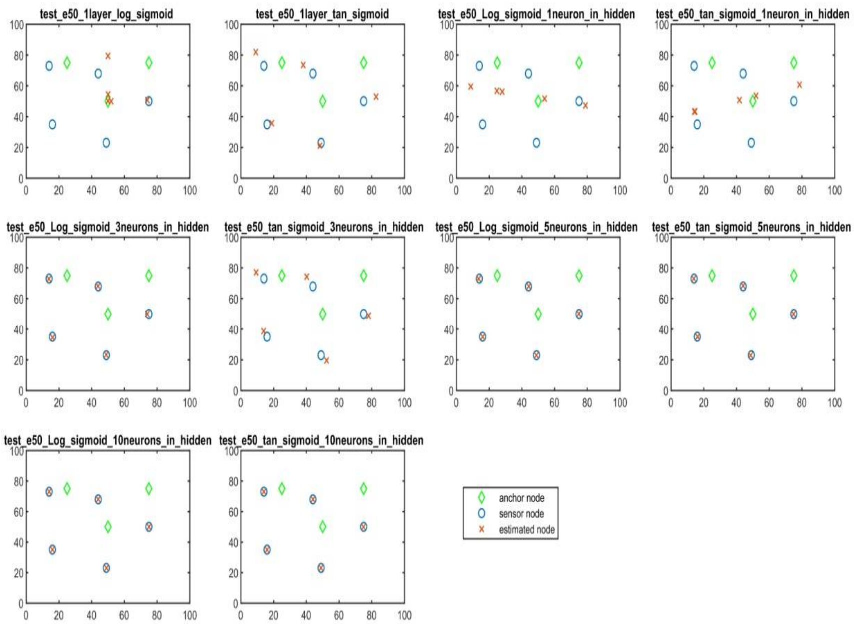

Figure (7) Outputs of case (e50) for localization of five nodes on the (100m x 100m) grid.

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Table (2) shows the actual locations of the five nodes used in the testing phase and the corresponding five outputs locations obtained from the designed networks.

Table (2) Actual locations of the five nodes used in testing

Output of neural network, Log_sigmoid of 5 neurons in hidden layer								Actual sensors location	
a100		a50		b50		c50			
14.074	73.059	11.886	47.645	29.729	51.932	13.034	79.688	14	73
15.971	34.981	11.873	47.096	18.121	31.944	15.451	31.299	16	35
43.987	67.993	45.722	48.944	59.503	55.429	38.146	60.749	44	68
49.014	23.018	51.512	50.400	30.222	39.528	70.801	43.026	49	23
74.971	49.978	85.519	54.625	66.937	60.790	67.918	41.213	75	50
d50		e50		f50		g50		Actual sensors location	
14.011	72.905	13.608	72.984	13.781	72.886	14.096	72.766	14	73
16.130	35.002	16.068	34.928	15.929	34.864	16.083	35.331	16	35
44.239	67.928	44.230	67.975	44.202	68.581	43.163	69.978	44	68
48.956	23.450	48.863	22.980	48.981	23.387	48.945	23.354	49	23
75.003	50.176	74.826	50.180	74.999	49.960	74.258	50.009	75	50

Table (3) shows the maximum, minimum and average errors for 6 output samples of different designed networks, while consisting of 2 layers, with a log sigmoid activation function in the hidden layer containing (5) neurons and a single output layer with a linear activation function.

Table (3) maximum, minimum and average errors for 6 output samples

The network	Max. error	Min. error	Avg. error
a100_Log_sigmoid_5neurons_in_hidden	0.07374	0.00654	0.07374
a50_Log_sigmoid_5neurons_in_hidden	27.39963	1.72153	27.39963
b50_Log_sigmoid_5neurons_in_hidden	21.06836	2.12114	21.06836
c50_Log_sigmoid_5neurons_in_hidden	21.80082	0.54860	21.80082
d50_Log_sigmoid_5neurons_in_hidden	0.45002	0.00222	0.45002
e50_Log_sigmoid_5neurons_in_hidden	0.39159	0.01629	0.39159
f50_Log_sigmoid_5neurons_in_hidden	0.58130	0.00072	0.58130
g50_Log_sigmoid_5neurons_in_hidden	1.97850	0.00926	1.97850

V. CONCLUSION AND FUTURE WORK

From the analysis of the results we obtained, we conclude the following:

1. The placement of the anchor node on the edges of the geographical area (100m x 100m) grid makes the transmission distance far away from some nodes in the network and this can lead to a more energy consumption for sending data, as, the greater the transmission distance, the greater energy consumed.
2. Anchor nodes on the edges of the geographical area increase the probability of not reaching the required signal level at other edges, thus losing of ability to obtain thier location, as there is a node away from the anchor nodes at a distance of 141.4213562 meters in case (a100), while the maximum ZigBee transmission range is 30 meters

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Vol. 6, Issue 10, October 2018

inside buildings and 100 meters for outside. Therefore, it is recommended to place anchor nodes with a distance of less than 100 meters from all other nodes to ensure signal detection.

3. The placement of anchor nodes on the outer boundary of the sensor area is not considered optimal form the point of view of using its coverage area because three-quarters of the anchor nodes are almost beyond the limits of the sensor area to be monitored.

Based on the obtained results, it has been found that placing one of the anchor nodes at the center of the wireless sensors network is the best choice to reduce the distance of the transmitter. In that choice, the second anchor node can be placed within the first half of the network, while the third node can be positioned within the second half of the network. It has been also noted that the cases (a50, b50, and c50) appear with the highest fault ratio even if the number of neurons in the hidden layers are increased. This leads us to conclude that the highest error rate has been faced when the anchor nodes are placed on a single straight line.

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