Development of A Wi-Fi Based Indoor Location System Using Artificial Intelligence Techniques

İsmail Kırbaş[1,*], Ayhan Dükkancı[2]
[1]*Department of Computer Engineering, Burdur Mehmet Akif Ersoy University, Istiklal Campus, 15100, Burdur, Turkey*
[2]*Department of Material Technologies Engineering, Burdur Mehmet Akif Ersoy University, Istiklal Campus, 15100, Burdur, Turkey*

***Abstract*—The main aim of this study is to resolve the problem of indoor positioning in closed areas, which has become a growing need nowadays, by using existing hardware solutions. Although the use of the GPS system, which requires satellite communication as an open space location solution, is very common, it cannot provide a solution for indoor. It is a well-known metric to measure signal strengths to determine distances between wireless nodes. However, the signal strength is affected by many external influences and causes erroneous measurements. With the developed approach, the transmission powers of the signals received from more than one transmitter located within a certain closed area are measured and given as an input to an artificial neural network. It has been seen that the outputs produced by the trained neural network are much more successful and reliable than the path-loss calculation.**

***Keywords*—artificial intelligence, artificial neural networks, wireless sensor networks, indoor navigation, indoor radio communication.**

I. INTRODUCTION

In real world applications, wireless sensor networks are becoming widespread and are used in many different areas. They afford remarkable facilities in installed environments such as site security, assisted living, home automation, health monitoring, military applications, environmental monitoring, etc. Indoor localization problem is also waiting for the most suitable solution in many fields of activity.

The positioning problem is generally divided into two parts. The first part is open-field positioning systems and is generally used to achieve successful results using the Global Positioning System (GPS) system. Thus, the position and speed of a moving object can be tracked within an open area. Supported by GPS system, GSM and UMTS systems can be used to track moving nodes. For example, when communicating with the GSM base stations used by the mobile phone user during communication, the signal strength is measured and accordingly the distance, direction and speed of the moving object can be estimated. Since the locations of the base stations are known precisely, the position of the user can be predicted using the triangulation technique. Again, if the user uses a smartphone and the GPS feature is supported on the device he / she uses, he / she can communicate directly with the GPS satellites and determine his / her position. However, it has a very high cost to use the GPS system and it cannot be used in covered areas.

Manuscript received December 12, 2018; accepted December 24, 2018.
*Corresponding author: ismailkirbas@mehmetakif.edu.tr

Since the use of GPS in closed area positioning systems is not possible, different approaches should be used. If the communication is made with a constant signal transmission power, the received signal strength can be measured. This approach brings the most cost-effective solution. Because there is no need to use extra hardware to measure signal strength. When the literature is examined, it is seen that techniques such as time-of-arrival (TOA), angle-of-arrival (AOA), time difference of arrival (TDOA) and received signal strength (RSS) are used for indoor positioning.

Wireless positioning systems can have two different configurations. The first one is the mobile assisted and the second one is the network-assisted method. In the mobile assisted approach, the mobile node tries to determine the nodes in which it can communicate around its position. In the network-assisted approach, the reference node measures the signals from the mobile node to transmit to the central processing unit in connection with the network, and the calculation operations are performed by the central processing unit.

There are many publications on wireless network positioning in the literature. Hara and Anzai [1] investigated the experimental results of known estimation methods. Results presented that RSSI has advantages over TDoA especially for a crowded area, where line of sight between the nodes are interrupted repeatedly. Chrysikos at al. [2] developed and indoor RSSI model called ITU indoor model for a specific site. Türkoral at al. [3] is intended to predict the distances between the nodes by using RSSI data and they developed distance estimation approach for two nodes using three different transmission models grounded on the RSSI metric data. Guan and Li [4] assert some enhancements to the traditional localization algorithm adding an error checking and correction method. Zhang at al. [5] put forward RSSI-based fingerprint feature vector algorithm, which splits covered area into grids, and access points are deployed. Mistry and Mistry [6] prepared a survey study aims to run several RSSI based localization methods for wireless sensor networks and indoor-outdoor applications. Livinsa and Jayashri [7] offers RSSI based localization algorithm to get better distance prediction for indoor positioning applications. They had better distance estimation for outdoor environment than indoor environment and achieved minimum localization error by using different number of anchor nodes. Vadivukkarasi and Kumar [8] suggested an approach based on RSSI measurement to decrease the estimation error for indoor location. They enhanced RSSI method to reach average 36% error reduction using various power levels and ensure better distance estimation. Chen [9] worked on indoor people positioning for health care applications using wireless sensor networks. They employed RSSI data, ML algorithm and ZigBee sensor nodes. Mesmoudi at al. [10] prepared a comprehensive survey on range-free and range-based localization algorithms for wireless sensor networks. Parameswaran at al. [11] also investigated whether RSSI is a reliable parameter for sensor localization algorithms. Kuntal at al. [12] arranged a survey on wi-fi-based location determination techniques.

Section 2 gives brief information on position estimating algorithms, section 3 describes the indoor location application, section 4 mentions developing an ANN for wi-fi fingerprinting method and finally, section 5 discusses the results.

II. POSITION ESTIMATION ALGORITHMS

Estimating coordinates of a node in a 2-D field requires communicating with at least three stations simultaneously. The WCL and the Trilateration algorithms, which are developed based on this idea, are briefly explained in following sections.

A. Path Loss Modelling

Path loss is the power density reduction of a radio signal as it transmits through space, and arithmetically, it can be described as the difference (in dB) between the sent radio wave power and the received radio wave power [13].

$$L = 10 \cdot \log(P_{tx}/P_{rx}) \tag{1}$$

where L represents the path loss in dB, is the transmission power of the transmit unit in Watts, and is the remaining power of received signal at the receiver unit.

Equation 2 can be used to make RSSI calculation easy when considered the path loss model [14].

$$RSSI = -(10n\, log_{10}d + A) \tag{2}$$

where n is signal transmission exponent or constant, A is the received signal strength value at 1 meter distance and d is the distance from signal transmitter.

B. Weighted Centroid Localization

The Centroid Localization (CL) algorithm estimates the unknown node coordinates simply by taking the average of the coordinates received from the transmitter antennas each of which broadcast their own position data [6]. The mathematical representation of the algorithm is given by [15]

$$P_i^{CL}(x,y) = (1/n)\sum_{j=1}^{n} B_j(x,y) \tag{3}$$

where is the estimated coordinates of the node, is the exact coordinates of the beacon where the beacons are the transmitter antennas each of which continuously broadcasts its own coordinates, and is the number of access points, coordinates of which are received by the node.

C. Trilateration

Consider a wireless node P with an unknown location (p_x, p_y) and three access points A, B and C, known as the positions (a_x, a_y), (b_x, b_y) and (c_x, c_y), respectively. If we know the coordinates of the all three access points A, B and C we can calculate the exact position of node P. Figure 1 depicts the problem clearly.

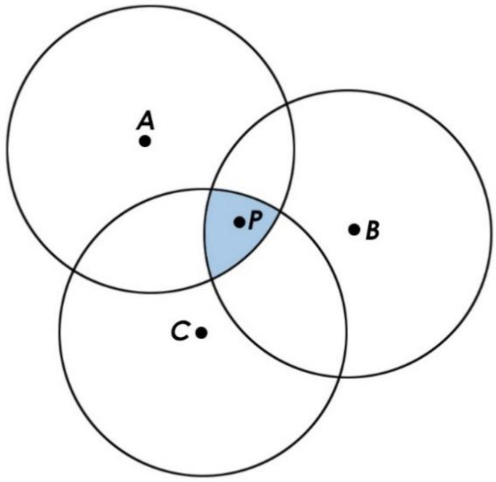

Fig. 1. Location calculation of the coordinate unknown wi-fi node with three access points.

Trilateration problem is to figure out the coordinates of node P, given distances d_a, d_b and d_c, from the node to access point A, B and C, respectively. Using the estimated distances from the node to the three wi-fi access points, the problem can be defined as in the following system of equations [13]:

$$(p_x - a_x)^2 + (p_y - a_y)^2 - d_a^2 = 0 \tag{4}$$
$$(p_x - b_x)^2 + (p_y - b_y)^2 - d_b^2 = 0 \tag{5}$$
$$(p_x - c_x)^2 + (p_y - c_y)^2 - d_c^2 = 0 \tag{6}$$

III. INDOOR LOCATION POSITIONING APPLICATION

In this study, we choose a 4-meter-wide and 15-meter long meeting room for the indoor positioning application. 6 wi-fi devices have been installed in certain places of the meeting room at certain intervals. Each wi-fi device acts as an access point for a different wi-fi network. Fig. 2 shows the drawing of the meeting room used in the experiment and the location of the wi-fi points.

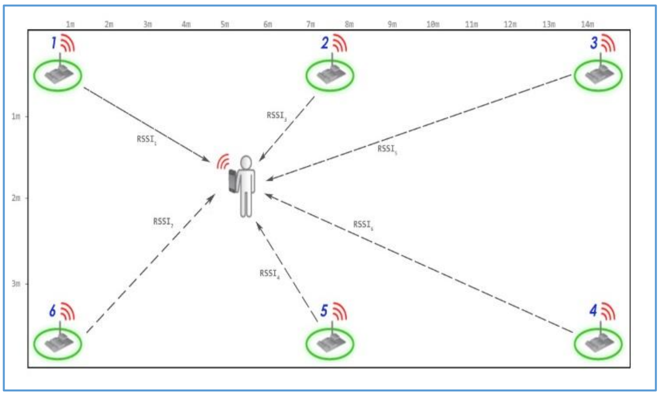

Fig. 2. Testbed for indoor location estimation experiment.

Figure 3 shows the device that measures the signal strength of these wi-fi points and records the results obtained through a web service. The person who will perform the measurement comes to certain positions and enters the position of the meter on the screen of the meter using the four buttons located on the left hand side. OLED display is used to monitor positioning data, data collecting and sending process.

The measuring instrument measures the signal strengths of the wi-fi devices in the room and sends them to the computer connected to the network. The measurement and recording process is repeated at 1 meter intervals. Thus, fingerprint data of all wi-fi devices are collected and a wi-fi signal strength map is obtained.

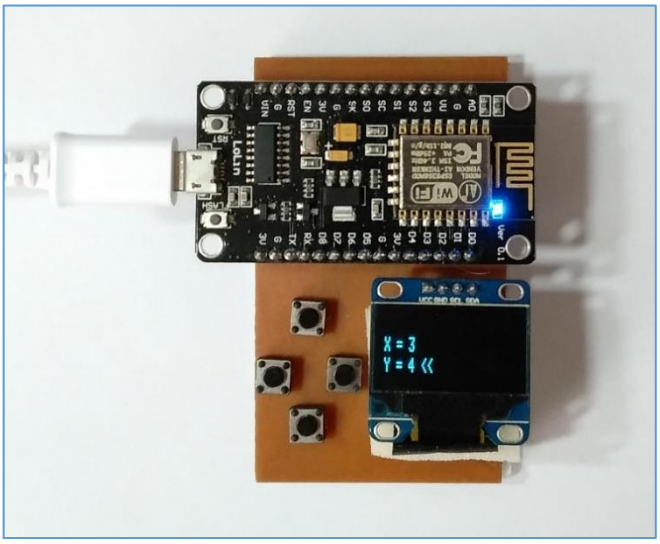

Fig. 3. wi-fi signal strength measurement device which consists of a NodeMCU development board and an OLED display.

The RSSI values measured by wi-fi devices range from -95 dBm to 0 dBm. In order to be easier to use in the presentation and calculation all measurement values have been increased by 100. The primary problem in RSSI-based motion monitoring is its very sensitive to environmental changes. The declining nature of RSSI measurement set bounds to precision and accuracy in prediction. RSSI measurement method is unreliable because there may be changes in signal strengths even if the transmitting and receiving devices have not moved. In Figure 4, RSSI values for all nodes were plotted using the scatter plot command in Matlab.

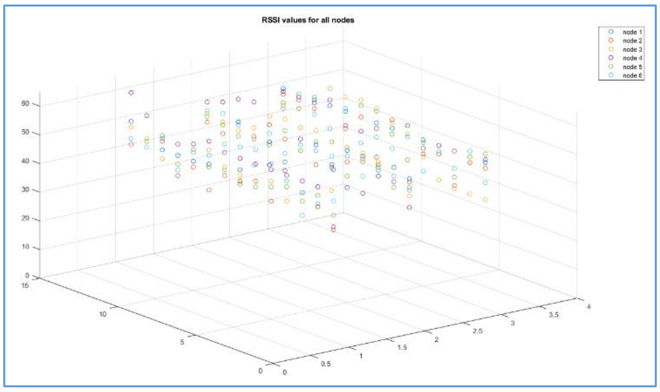

Fig. 4. Scatter plot of RSSI values for all nodes.

Scatter plot drawing becomes unintelligible when the number of node data increases. The heat-map approach was used to make the data more meaningful. Figure 5 indicates a map of the RSSI signalling powers for station 1 and Figure 6 depicts the RSSI signal strength map for station 2.

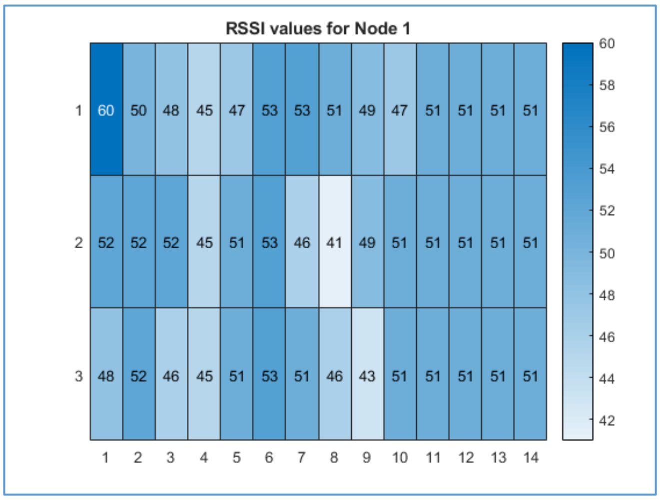

Fig. 5. RSSI heat-map presentation for wi-fi node 1, which is located in a (3m by 14m) room.

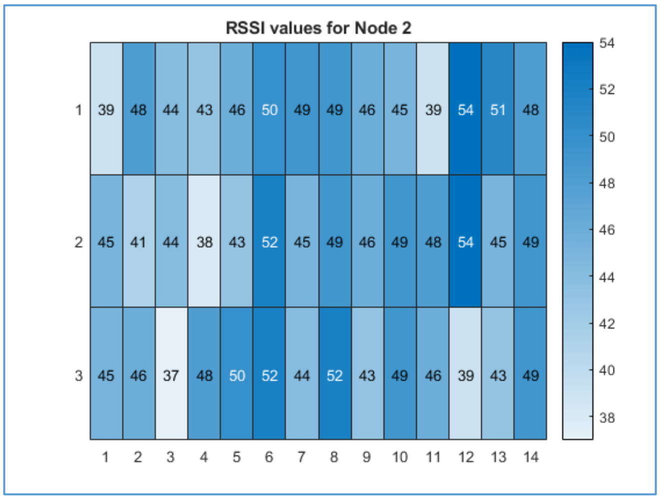

Fig. 6. RSSI heat-map presentation for wi-fi node 2, which is located in a (3m by 14m) room.

IV. DEVELOPING AN ANN FOR WI-FI FINGERPRINTING METHOD

As shown in Figures 5 and Figure 6, the RSSI values are not linearly distributed. This situation reduces the validity of equation 1. That is, it is very difficult to detect the distance between two nodes by measuring only the signal strength. As a solution to this problem, an artificial neural network was established using the wi-fi fingerprint technique. The input values of the artificial neural network are the RSSI levels measured from the nodes, and the output value is the coordinate information of the measuring device. Neural Network application of Matlab program has been used to create artificial neural network model. Figure 6 indicates the structure of the artificial neural network developed. Accordingly, the network has 6 inputs, 2 outputs and 20 neurons in the hidden layer. Levenberd-Marquardt was selected as the training method and the data set was randomly segmented. The Mean Square Error (MSE) parameter [16] was also used to measure the training performance of the network. Equation 7 gives MSE calculation for backpropagation performance.

$$MSE = \frac{1}{N}\sum_{i=0}^{N}\sqrt{(x-\hat{x})^2+(y-\hat{y})^2} \qquad (7)$$

The trained artificial neural network is an Multi Layer Perceptron (MLP) network which consists of three layers of nodes in a directed graph. In this approach, each layer fully connected to next layer. Because of this they are called fully connected network. The nodes in the hidden layer performs the most important task during the training process. Incorrect weight values are updated using the backpropagation algorithm. Each node in one layer connects with a certain weight wij to every node in the following layer. Output layer calculation is shown in Equation (8)[17].

$$y_i = f\left(\sum_{j=1}^{m} w_{ij}x_j + b_j\right) \qquad (8)$$

Figure 7, depicts main architecture of the developed artificial neural network.

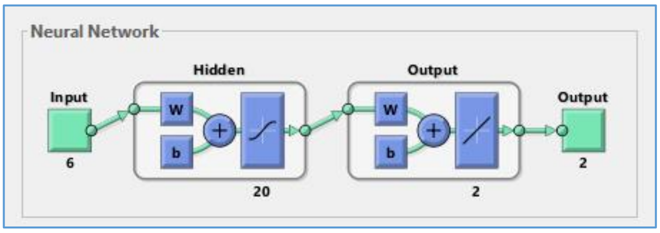

Fig. 7. Architecture of the developed artificial neural network.

70 percent of the collected data were used for training, 15% for testing and the remaining 15% for validation. Whole data set contains 103 measurements. At least two measurements were made at each point to ensure data validity. Figure 8 shows the MSE error graph calculated during training process.

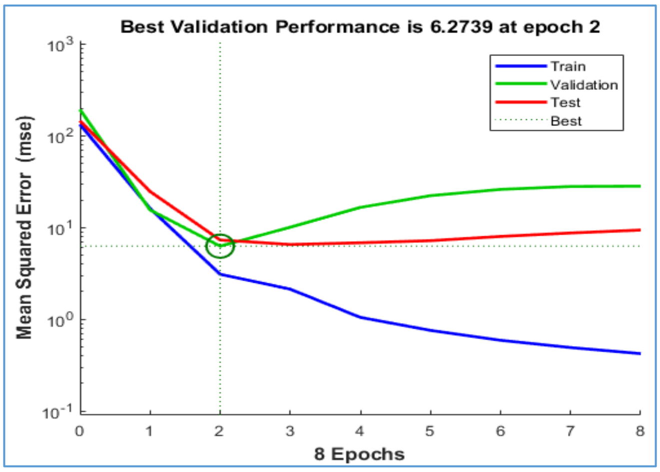

Fig. 8. MSE values for training, validation and test process.

In Figure 9, there is an error histogram of the trained network. The error histogram data is uniformly distributed. There is no accumulation on the right or left hand side.

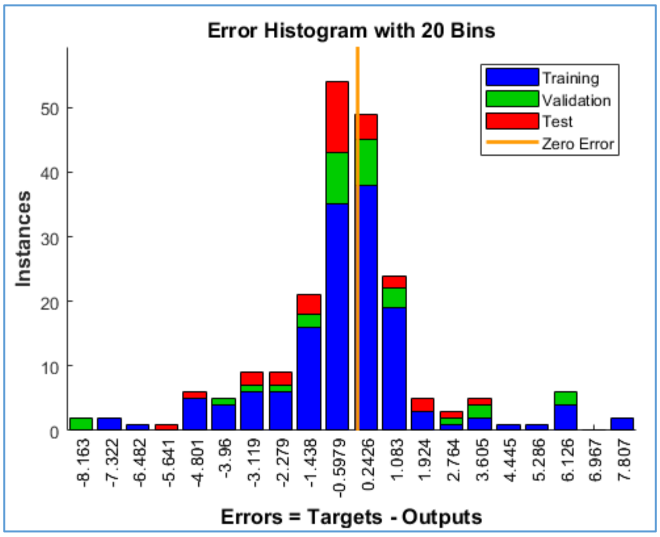

Fig. 9. Error histogram for the trained ANN outputs.

V. CONCLUSION

Figure 10, shows the performance of education validity and test results. Accordingly, the average performance of the trained network was calculated as 0.87. The goal here is to reach the value 1. However, even at the same point different RSSI values are measured and the use of these values for education causes deviations in the results. The developed model has more reliable results compared to the logarithmic calculation method.

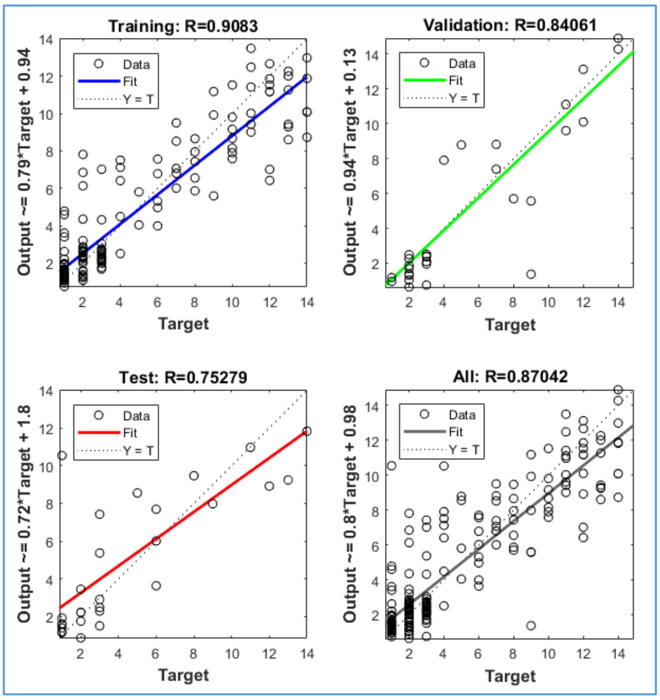

Fig. 10. Training, validation and test performance graphics for the trained ANN.

In order to increase the sharpness of the application more wi-fi nodes can be add, or the artificial neural network can be re-trained with different parameters. Some smoothing techniques can be applied during the collection of RSSI data.

In this study using RSSI data, fingerprinting technique is combined with artificial neural network application which is an artificial intelligence approach. At the same time, a reliable measurement technique has been introduced for indoor positioning without using any extra equipment and without creating extra energy costs. The results are very promising for future studies.

ACKNOWLEDGMENT

This research is supported by KOSGEB Research & Development Innovation and Industrial Application Support Program,grant 2018/620-5/01.

REFERENCES

[1] [1] S. Hara and D. Anzai, "Experimental Performance Comparison of RSSI- and TDOA-Based Location Estimation Methods," in VTC Spring 2008 - IEEE Vehicular Technology Conference, 2008, pp. 2651–2655.

[2] [2] T. Chrysikos, G. Georgopoulos, and S. Kotsopoulos, "Site-specific validation of ITU indoor path loss model at 2.4 GHz," in 2009 IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks Workshops, 2009, pp. 1–6.

[3] [3] T. Türkoral, Ö. Tamer, S. Yetiş, E. İnanç, and L. Çetin, "Short Range Indoor Distance Estimation by Using RSSI Metric," Istanb. Univ. - J. Electr. Electron. Eng., vol. 17, no. 2, pp. 3295–3302.

[4] [4] B. Guan and X. Li, "An RSSI-based Wireless Sensor Network Localization Algorithm with Error Checking and Correction," Int. J. Online Eng. IJOE, vol. 13, no. 12, p. 52, Dec. 2017.

[5] [5] A. Zhang, Y. Yuan, Q. Wu, S. Zhu, and J. Deng, "Wireless Localization Based on RSSI Fingerprint Feature Vector," Int. J. Distrib. Sens. Netw., vol. 2015, pp. 1–7, 2015.

[6] [6] H. P. Mistry and N. H. Mistry, "RSSI Based Localization Scheme in Wireless Sensor Networks: A Survey," in 2015 Fifth International Conference on Advanced Computing Communication Technologies, 2015, pp. 647–652.

[7] [7] Z. M. Livinsa and S. Jayashri, "Performance analysis of diverse environment based on RSSI localization algorithms in wsns," in 2013 IEEE Conference on Information Communication Technologies, 2013, pp. 572–576.

[8] [8] K. Vadivukkarasi and R. Kumar, "A New Approach for Error Reduction in Localization for Wireless Sensor Networks," 2012.

[9] [9] Y. Chen, L. Zhang, and J. Wang, "Localization indoor patient in wireless sensor networks," in 2013 First International Symposium on Future Information and Communication Technologies for Ubiquitous HealthCare (Ubi-HealthTech), 2013, pp. 1–3.

[10] [10] A. Mesmoudi, M. Feham, and N. Labraoui, "Wireless Sensor Networks Localization Algorithms: A Comprehensive Survey," Int. J. Comput. Netw. Commun., vol. 5, no. 6, pp. 45–64, Nov. 2013.

[11] [11] A. T. Parameswaran, M. I. Husain, S. Upadhyaya, and others, "Is rssi a reliable parameter in sensor localization algorithms: An experimental study," in Field Failure Data Analysis Workshop (F2DA09), 2009, p. 5.

[12] [12] A. Kuntal, M. L. Tetarwal, and P. Karmakar, "A Review of Location Detection Techniques in Wi-Fi," 2014.

[13] [13] F. İleri and M. Akar, "RSSI Based Position Estimation in ZigBee Sensor Networks," Signal Process. Commun., p. 12.

[14] [14] A. Paul and T. Sato, "Localization in Wireless Sensor Networks: A Survey on Algorithms, Measurement Techniques, Applications and Challenges," J. Sens. Actuator Netw., vol. 6, no. 4, p. 24, Oct. 2017.

[15] [15] N. Bulusu, J. Heidemann, and D. Estrin, "GPS-less low-cost outdoor localization for very small devices," IEEE Pers. Commun., vol. 7, no. 5, pp. 28–34, Oct. 2000.

[16] [16] M. Duhan, "Study of Localisation Methods of Mobile Users in Wireless Sensor Networks," vol. 3, no. 6, p. 6, 2014.

[17] [17] İ. Kırbaş and A. Kerem, "Short-Term Wind Speed Prediction Based on Artificial Neural Network Models," Meas. Control, vol. 49, no. 6, Jul. 2016.