International Journal of Business Data Communications and Networking
Volume 19 • Issue 1 • January-December 2024

Distance-Based Localization in Wireless Sensor Network Using Exponential Grey Prediction Model

Dipak W. Wajgi
Department of Computer Engineering, St. Vincent Pallotti College of Engineering and Technology, Nagpur, India

Jitendra V. Tembhurne
Department of Computer Science and Engineering, Indian Institute of Information Technology, Nagpur, India

Rakhi D. Wajgi
Department of Computer Technology, Yeshwantrao Chavan College of Engineering, Nagpur, India

ABSTRACT

Localization in wireless sensor network is the key for many applications in which location of occurrence of event is very important. Distance based localization techniques have proved to be more accurate and feasible for the location calculation of the sensor nodes. Moreover, Received Signal Strength Indicator (RSSI) based techniques are well adopted by the researcher to calculate the distance between the sensor nodes. The optimized value of RSSI may estimate the location more precisely. In this paper, Exponential Grey prediction model and weighted predicted RSSI values are utilized to provide estimated values of RSSI which are then optimized using an objective function. The decreasing term used in the differential equation of the Grey prediction model provides better prediction accuracy which if optimized provides efficient result. The conventional Grey prediction model is limited by the sample space and scope of applications. The Exponential Grey prediction model used in the proposed algorithm removes those drawbacks and can be applied in real time applications with larger sample space. The objective function used in the proposed algorithm uses weighting factor to be applied to Grey predicted RSSI and weighted predicted RSSI to estimate the RSSI value more accurately. The objective function calculates more near values of RSSI to localize the node more accurately. The simulation results obtained are compared with the latest techniques of RSSI calculation like weighted centroid method, RSSI quantization, TMA and FRBW algorithm. The results show that the proposed algorithm outperform the existing methods for RSSI estimation.

KEYWORDS

Localization, RSSI, Grey Prediction, Wireless Sensor Networks, Objective Functions, Exponential Grey Prediction

1. INTRODUCTION

Wireless sensor network (WSN) consists wireless sensor nodes which are deployed randomly or deterministically in the area of study. These nodes are small, less in energy, inexpensive and multifunctional connected wirelessly. These nodes are used to sense the temperature, light, pressure, humidity, etc. from the environment. Sensor nodes can perform some computation and they can communicate with other sensor nodes present in the network. Performance of WSN depends on many

DOI: 10.4018/IJBDCN.353393

parameters such as deployment strategy, location identification strategy, routing algorithms applied for data communication and data aggregation strategies (Elayan et al. 2018 and Pal 2010). Sensor nodes are unaware about their location in the network during deployment. The location information can be obtained by applying some location identification process. Location information is needed for applications such as designing efficient routing algorithms, finding the coverage of the network and load balancing in the network (Elayan et al. 2018, Tomic et al. 2017 and Pal 2010). Moreover, adding Global Positioning system (GPS) to all sensor nodes is not feasible since it adds extra cost to the hardware. It also suffers from line-of-sight problem, size of the sensor node is increased and reduces the battery life of the network. A cost-effective solution is required which can be utilized in diverse environments (Tomic et al. 2017). Many distance estimation techniques have been proposed to calculate the position of the sensor node in WSN. Received Signal Strength Indicator is one of the cheap and flexible solution which measures the signal strength at the receiver node. The propagation loss is calculated based on known transmission power. Distance calculation models can be adopted to convert this propagation loss into distance estimation. In addition, RSSI method is employed for radio frequency signals. Also, RSSI is less expensive as compared to other methods since it does not require any additional hardware but it suffers from multipath propagation of radio signals (Pal 2010, Paul et al. 2017, Bal et al. 2009, Flammini et al. 2006).

Using the calculation of RSSI, numerous distance estimating approaches have been presented. Grey prediction technique provides some better results as compared to other RSSI estimation techniques. But normal grey prediction techniques have limited scope as far as the sample space is concerned and can be applied in limited applications. While Exponential Grey prediction has a large sample space and has broader application areas. Moreover, Exponential Grey prediction provides more accurate values than the normal grey prediction technique. The efficiency and better accuracy of Exponential Grey prediction technique is the key motivation for using this technique for RSSI prediction. Better distance and location estimation of the sensor nodes will result from more accurate RSSI value prediction. This estimation is further optimized using optimization function which can help in precisely locating the sensor node by using any localization technique.

The remainder of the paper is organized as follows. Section 2 discusses the literature based on distance calculation algorithm using RSSI estimation. The mathematical modeling of Exponential Grey prediction model is described in section 3. The proposed algorithm is presented in section 4. Section 5 illustrate the experimental results, analysis and comparison with the existing techniques. Conclusion is described in Section 6 along with the future scope of the research.

2. RELATED WORKS

The distance-based localization algorithms which uses received signal strength Indicator (RSSI) information to estimate the distance and the location information, are discussed in this section.

The edge weights of the anchor nodes are determined by the Received Signal Strength (RSS) value. It is also used to calculate the distance between network nodes. Moreover, to reduce the localization error, an Invasive Weed optimization is utilized (Sharma et al. 2018). Further, to reduce the uncertainty and non-linearity between the received signal intensity and the distance, fuzzy logic is applied. The edge weights are created using a fuzzy logic method. These edge weights are optimized using Invasive Weed. As indicated in Equation (1), the coordinates of the target node are computed using the edge weights of the anchor nodes.

$$(x_t\ , y_t) = \left[\frac{(w_1x_1) + \dots (w_nx_n)}{\sum_{i=1}^{k} w_i}\ ,\ \frac{(w_1y_1) + \dots (w_ny_n)}{\sum_{i=1}^{k} w_i}\right] \tag{1}$$

Localization error (LE) is computed using Equation (2) where x_e and y_e are the coordinates of the target node estimated by the algorithm, x_a and y_a are the actual coordinates of the target nodes and n is the total number of target nodes.

$$LE = \sqrt{(x_e - x_a)^2 + (y_e - y_a)^2} \tag{2}$$

Equation (3) calculates the average localization error (ALE).

$$ALE = \frac{\sqrt{(x_e - x_a)^2 + (y_e - y_a)^2}}{n} \tag{3}$$

The RSS ratio of the anchor node and virtual reference node has been used to determine the position of user nodes by renewing the signal strength information as the environment changes (Xu et al. 2008). Curve fitting and intersections are introduced as additional reference nodes. Increasing the number of references available as illustrated in Equation (4), signal strength (SS) at distance d is computed as

$$SS_d = P_T - P_L(d) \tag{4}$$

Where,

$$PL(d) = PL(d_0) - 10nlg\left(d/d_0\right)$$

Equation (5) is applied to compute the signal strength of the receiving node from the reference node in relation to the base station.

$$\begin{cases} SS_{i0} = R - P_L(G_i) = R - P_L(d_0) - 10n\lg\left(\sqrt{x_i^2 + y_i^2} \Big/ d_0\right) \\ SS_{i1} = R - P_L(G_i) = R - P_L(d_0) - 10n\ lg\left(\sqrt{(D - x_i)^2 + y_i^2} \Big/ d_0\right) \\ SS_{i2} = R - P_L(G_i) = R - P_L(d_0) - 10n\ lg\left(\sqrt{x_i^2 + (D - y_i)^2} \Big/ d_0\right) \end{cases} \tag{5}$$

Accordingly, the signal strength ratio is calculated as shown in Equation (6)

$$\begin{cases} SSR_{i1} = {SS_{i0}} \Big/ {SS_{i1}} = \dfrac{R - P_L(d_0) - 10n\lg(\sqrt{x_i^2 + y_i^2}/d_0)}{R - P_L(d_0) - 10n\lg(\sqrt{(D - x_i)^2 + y_i^2}/d_0)} \\ SSR_{i2} = {SS_{i0}} \Big/ {SS_{i2}} = \dfrac{R - P_L(d_0) - 10n\lg(\sqrt{x_i^2 + y_i^2}/d_0)}{R - P_L(d_0) - 10n\lg(\sqrt{(D - x_i)^2 + y_i^2}/d_0)} \end{cases} \tag{6}$$

Only under particular cases, like base station relocation, does the Received Signal Strength Ratio (RSSR) data need to be constructed. The algorithm is more adaptable and practical, and it works well in changing environments.

An empirical investigation of RSSI estimate in low-cost commercially accessible transceivers operating in the 2.4 GHz-ISM band was undertaken for the experimentation (Flammini et al. 2006). The RSSI is utilized to detect a busy channel and acts as an ON/OFF indicator, according to the findings. Here, hardware quality and preparatory calibration can improve the algorithm's performance, resulting in more accurate sensor node placement calculations.

With a Gaussian filter, the least square support vector regression localization procedure is investigated. The RSSI value with significant error is filtered out using the Gaussian function (Xia et al. 2019). The system searches for a more precise RSSI value in order to calculate the distance between unknown nodes and anchor nodes. To improve location accuracy, the algorithm employs a larger number of anchor nodes, Mean Location Error (MLE) is computed and further reduced as the number of anchor nodes increases. The conversion of quadratic regression into linear, equality simplifies the location calculations of unknown nodes. The algorithm's kernel function provides a good regression effect that works in both small and big samples. With RSSI ranging, a Gaussian function is employed to improve calculation accuracy.

The position calculation in an outdoor communication channel in WSN is improved using a new statistical channel model based on the second moment of RSSI (Alavijeh et al. 2018) wherein two eventualities are considered. The simulation begins with the hidden node acting as a fixed node, and then switches to the hidden node acting as a mobile node. In all instances, three anchor nodes are employed to calculate the location of the unknown node.

The average energy of the received beacon node is utilized to improve sensor node location accuracy (Yaghoubi et al. 2014). The accuracy parameter is the squared position error bound, utilized to maximize the algorithm's performance. To make it energy efficient, an optimization problem has been created to minimize power usage while obtaining a certain level of localization accuracy. The best power allocation is achieved by examining two scenarios – with and without anchor node position uncertainty. By averaging the energy from the beacon node, the uncertainty problem of RSS is avoided. The error variance of the anchor node locations is assumed to be the same. By allocating transmission power optimally, significant reductions in power usage can be realized.

The unknown node in a WSN is located using a single anchor node technique (Rashid et al. 2013) and LUSA – a grid environment is utilized. Sensors are placed in a grid arrangement, with beacon nodes, special nodes, and unknown nodes, being the three categories of nodes specified. Beacon nodes are GPS-enabled and can locate their own location. Special nodes are positioned perpendicular to the beacon node and define their position in relation to it. Unknown nodes have no idea where they are. For example – location of a beacon node is broadcast, special node uses RSSI to calculate their distance from the beacon node and estimates their coordinates in relation to the beacon node. Special nodes also operate as beacon nodes after computing their location information, and unknown nodes compute their location information using the trilateration process. Further, location error can be computed using Equation (7).

$$\bar{Error} = \frac{\sum_{i=1}^{N-R} \left\| \hat{\theta}_i - \theta_i \right\|}{N - R} \tag{7}$$

Where, $\hat{\theta}_i$ is estimated location, θ_i is actual location, N is the total number of nodes in the network, and R is number of Beacon nodes. To minimize the localization error, a beacon node might be put in the center or corner of the grid.

The properties of RSSI have been studied in relation to essential environmental elements such as temperature, sensor node height, antenna type, and object electromagnetic interference (Xu et al. 2014). Experimentation is carried out to investigate the impact of environmental temperature on wireless quality. It has been discovered that the attenuation of RSS varies by around 5.0 dBm for every 10° of temperature variation. Higher temperature is associated with greater attenuation, regardless of the distance between the sensor nodes. The type of antenna utilized in the sensor nodes also affects the RSSI value. All of the experiments are conducted in a restricted setting with a clear line of sight and no obstructions. It is also observed that RSSI value may be influenced by the factors such as humidity and brightness.

In (Yun et al. 2009), two adaptive range-free localization techniques have been developed to locate the sensor nodes in WSN wherein soft computing approach is applied for localization. To collect the essential information for localization, these techniques do not require any sophisticated hardware, only RSS data is sufficient to estimate the position by sensor nodes. Further, each anchor node's edge weight is taken into account by the proposed algorithm. The location of sensor nodes is computed using a combination of edge weights. To simulate the edge weights – fuzzy logic system is utilized and genetic algorithm is applied for optimization. The other approach treats the problem of localization as if it were a single problem. It employs a neural network to evenly estimate the mapping between anchor node signals and senor node locations.

In (Li et al. 2018), efficient indoor positioning technology with Bluetooth beacon positioning has been developed. The back propagation neural network (BPNN) optimized by particle swarm optimization (PSO) is applied to train the RSSI distance model to reduce the positioning error. Authors has claimed that the proposed method offers better positioning accuracy than the traditional method wherein RSSI Real-time Correction algorithm is implemented. In addition, the Kalman filtering is adopted to smooth the RSSI. The distance between the blind node and the anchor node is estimated using the RSSI distance model trained by PSO-BPNN. RSSI distance measurement generally uses the logarithmic distance path loss model, expressed as follows:

$$RSSI = -10n\lg\left(\frac{d}{do}\right) + A + X\sigma \tag{8}$$

Where, d is the distance between transmitter and receiver. n is a path loss parameter, A is the RSSI with distance do. $X\sigma$ is a gaussian-distribution random variable with mean 0 and variance $\sigma 2$.

For convenience of calculation, do usually takes a value 1 meter. Since, $X\sigma$ has a mean 0, the distance path loss model can be obtained with:

$$R\bar{S}SI \ = \ -10nlog(d) + \overline{A} \tag{9}$$

Where, $\bar{A}$ is the average measured RSSI

In order to reduce the positioning error caused by RSSI fluctuation, the RSSI fluctuation in real time through the Bluetooth gateway is monitored. Bluetooth anchor nodes, Bluetooth gateway and mobile phone as blind node are utilized for the experimentation. In the offline phase, the average RSSI distance model is obtained as;

$$R\bar{S}SI \ = \ -10nlog(d) + \overline{Al} \tag{10}$$

In the online phase,

$$R\bar{m}l \ = \ -10nlog(dl) + \overline{A}l \tag{11}$$

The real time distance model is

$$Rml = -10nlog(dl) + Al \tag{12}$$

For Blind Node (N), the average signal strength and the real time signal strength is represented as;

$$\bar{R}_{Nl} = -10n\lg\left(d_{Nl}\right) + \overline{A}_{l} \tag{13}$$

$$R_{Nl} = -10n\lg\left(d_{Nl}\right) + A_{l} \tag{14}$$

Using above equations, a new relation can be devised

$$R_{Ml} - \overline{R}_{Ml} = A_l - \overline{A}_l = \Delta A_l \quad (15)$$

Where, ΔA_l represent the real time fluctuation of the Bluetooth system which is RSSI correction offset. The corrected RSSI is obtained as:

$$\widetilde{R}_{Nl} = R_{Nl} - \Delta A_l = -10n\log(d_{Nl}) + \overline{A}_l \quad (16)$$

This is the real time path loss model.

RSSI based iterative weighted centroid method is developed in (Akhil et al. 2021) for location estimation. Six anchor nodes and one sensor nodes is utilized to form a group of three anchor nodes to locate the sensor node. Location estimation is performed by using the sum of weighted factor multiplied by *x*- and *y*-coordinates separately. The following formulas are applied for the calculation.

$$X = \frac{(X_1 * P_{r1}) + (X_2 * P_{r2}) + (X_3 * P_{r3})}{P_{r1} + P_{r2} + P_{r3}} \quad (17)$$

$$Y = \frac{(Y_1 * P_{r1}) + (Y_2 * P_{r2}) + (Y_3 * P_{r3})}{P_{r1} + P_{r2} + P_{r3}} \quad (18)$$

Where, P_r is the RSSI value, X_1, X_2, X_3 are the x-coordinates of the anchor1, anchor2 and anchor3, respectively. Likewise, Y_1, Y_2, Y_3 are the y-coordinates of the anchor1, anchor2 and anchor3, respectively.

The error between the modified estimation and the measured values is obtained by using Equation (19).

$$Error = \frac{OriginalLocation - CalculatedLocation}{OriginalLocation} \quad (19)$$

An improved RSSI using Kalman filter to develop filtered RSSI with beacon weight approach is presented (Alsmadi et al. 2021). Three or more beacons are utilized to estimate the location of the object by calculating the distance using RSSI measurement from beacons. Kalman filter is applied to smooth out the RSSI values. Centroid localization and weighted centroid localization algorithms are applied on the smoothed RSSI. Here, beacon weight value depends on the distance between the beacon and the mobile node. Smaller the distance, more is the weight and vice versa. The error in position estimation is calculated as:

$$Position_{error} = \sqrt{(x_{est} - x_0)^2 + (y_{est} - y_0)^2} \quad (20)$$

Fingerprinting technique using improved RSSI is proposed (Jain et al. 2021) where the augmented data is classified by machine learning (ML) technique. The multipath propagation of the signal is avoided by augmenting the RSSI data and thus increases the localization precision by reducing the computation cost. Fingerprinting technique divides the area of interest into small rectangular shapes where the tagged RSSI measurement is mapped with location information obtained from the training data.

The outlier detection method is adopted in (Chuku et al. 2021) for removing the shadowing effect caused by the natural or man-made obstacles. Three different types of outlier detection techniques have been presented. The majority rule scheme uses the majority decision of the beacons to agree on the location estimation. Here, centroid based outlier detection scheme uses simple clustering technique to group the sensor into small groups to increase the accuracy of the location estimation. The clustering is employed to filter out the measured data points for effective estimation of the node location. Mean shift clustering based outlier detection technique uses non parametric sliding window mechanism to find the region which is best fit for the data points and finds the centroid of the region to estimate the location of the node more accurately.

In (Yin et al. 2021), distributed location estimation is presented using the Bayesian sensor fusion approach. The sensor node location is locally estimated using RSSI measurement with Kalman filter. A unique distributed technique is proposed that integrates soft signals from selected sensors and computes approximated Bayesian estimates to the true position. The covariance matrix is utilized to calculate the total variance from the RSSI measurements and roughly estimate the position of the unknown node. The fusion approach is applied to find the estimated location of the sensor node.

Localization in WSN based on RSSI quantization and the genetic algorithm is presented (Ren et al. 2020). During RSSI quantization, the ring width is determined by applying the genetic algorithm on divided nodes sensing disks into multiple rings. Density based clustering is used to remove the ambiguity between the overlapping areas formed after performing mapping. The two-stage centroid algorithm is used to perform location estimation of the nodes in the sensor network with irregular network area. Three mobile anchor nodes are used to locate the node in the sensor network forming a triangle (Ibrahim et al. 2020). These mobile anchors are chargeable to deal with the energy efficiency problem in the network. Relative Side Coordinates (RSC) method using RSSI is used to find the distance information.

3. MATERIALS AND METHODS

In this section, the detailed description of Exponential Grey prediction model along with its mathematical modeling is presented and optimization function is proposed. The normal grey prediction algorithm is widely used for predicting the values in many applications but it has some limitations as far as the application area and the sample space is concerned. The Exponential Grey prediction is the mathematical model for predicting the values and is efficient and accurate as compared to normal grey prediction techniques. The optimization function can be applied to increase the prediction accuracy and efficiency of Exponential Grey prediction technique for obtaining better results. In this section, the Exponential Grey prediction technique along with the proposed optimization function is described which enhance the accuracy of prediction and increases the efficiency of algorithm.

3.1 Exponential Grey Prediction Model (EXGPM)

Grey theory involves system analysis, prediction, and control, and also helps in decision making. This theory categorize the information in white, black and grey classes depending on known, unknown and semi-known information. Metrology, agriculture, military application and remote sensing are the key application areas where this model is used as the prediction model. The semi-known or grey information in this model refers to the unreliable or shortage of information. Grey prediction model produces better results over time series data where generally linear equations are used. But it also provide maximum efficiency with the fractional computations (Baloochian et al. 2020).

Grey theory is utilized as prediction model in the proposed algorithm since it provides better results in limited sample space and is suited for forecasting applications. Grey prediction method along with RSSI is applied for localization in WSN. Grey prediction is adopted to predict the tendency of RSSI at run time and reduces the fluctuation of RSSI when sensor node is moving. The exponential function used in grey prediction reduces the error of prediction and provides better results (Bilgil 2021). Predicted RSSI is calculated based on received RSSI using grey prediction.

Radio Propagation Model:

$$RSSI(d) = RSSI\left(d_0\right) - 10n\log\left({}^{d}\!/_{d_0}\right) \tag{21}$$

$$\hat{d} = d_0\, 10^{\frac{RSSI(d_0)-RSSI(d)}{10n}} \tag{22}$$

$$\hat{d} = d + X_\sigma \tag{23}$$

The basic Grey Prediction model considers the following - $X^{(1)}$ is accumulated generating operation,

$$x^{(1)}(k) = \sum_{m=1}^{k} x^{(0)}(m), \qquad k \in \{1, \ldots, n\} \tag{24}$$

The prediction equation is given as;

$$\hat{x}^{(1)}\,(k+1) = \left(x^0\,(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \tag{25}$$

Where, the whitening equation is modeled as;

$$\frac{dx^{(1)}}{dt} + a x^{(1)} = b \tag{26}$$

A key feature of the exponential grey forecasting model is the raw data's exponential change. When the raw data sequence's exponential variation is separated, it's clear that the grey action amount is time dependent, and its change is exponential with time.

The linear differential equation is the whitening equation of EXGPM, expressed as;

$$\frac{dX^{(1)}(t)}{dt} + aX^{(1)}(t) = b + c\,e^{-t} \tag{27}$$

The Grey derivative for the first order differential equation in its intermediate form can be represented as;

$$\frac{dx^{(1)}(t)}{dt} = \lim_{x\to 0} \frac{x^{(1)}(t+\Delta t) - x^{(1)}(t)}{\Delta t} \tag{28}$$

Where, Δt is the increment in time.

The Equation (21) can be approximated to the following;

$$\frac{dx^{(1)}(t)}{dt} \approx x^{(1)}\left(k+1\right) - x^{(1)}\left(k\right) = x^{(0)}\left(k\right) \tag{29}$$

$$x^{(0)}(k) + a z^{(1)}(k) \; = \; b + c(e-1)e^{-k} \tag{30}$$

is the basic difference equation of EXGPM, where, $z^{(1)}(k)$ is given as;

$$z^{(1)}(k) = \frac{x^{(1)}\,(k) + x^{(1)}(k-1)}{2} \quad k \; = \; 2,3,\ldots\ldots.n \tag{31}$$

The solution of the linear equation can be derived as follows;

$$x^{(1)}\left(k\right) = \frac{b}{a} + \frac{c}{a-1}e^{-t} + d\,e^{-at} \tag{32}$$

Where, d is the integral constant. By considering the initial condition $x^{(1)}(1) = x^{(0)}(1)$ the constant d can be calculated as;

$$d \; = \; \left(x^{(0)}(1) - \frac{b}{a} - \frac{c}{a-1}e^{-1} \right) e^{a} \tag{33}$$

So, the predicted values of the original series $\hat{x}^{(0)}(k)$ can be obtained as;

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(01)}(k-1) \quad k \; = \; 2,3,\ldots\ldots..n \tag{34}$$

Mean square error can be calculated as;

$$MSE \; = \; \frac{1}{N}\sum_{i=1}^{N}\sqrt{\left(x_i - \hat{x}\right)^2 + \left(y_i - \hat{y}\right)^2} \tag{35}$$

3.2 Optimization Function

The accuracy of the grey prediction estimation can be increased by applying some optimization function on the predicted values. The optimization function provides more real and accurate estimation when compared to the measured values. The grey predicted values and the weighted predicted estimation are used to obtain the optimized values.

This optimization function is devised by applying some edge weights to the predicted values and the weighted predicted values. The weights applied are decided by observing the nature of data.

The estimated optimized RSSI values can be obtained by using the objective function which is given as below:

$$PRSSI \; = \; \frac{2 * PrRSSI + WRSSI}{3} \tag{36}$$

Here, *PrRSSI* is the predicted value of RSSI using Exponential Grey prediction model and *WRSSI* is the weighted predicted RSSI value.

This objective function combines the grey predicted RSSI and weighted predicted RSSI values to give more accurate value of RSSI which can be utilized to localize the sensor node.

The mean square error between the measured RSSI (MRSSI) and proposed RSSI (PRSSI) is calculated as follows:

$$MSE1 \; = \; \frac{1}{N}\sum_{i=1}^{N}\sqrt{(PRSSI - MRSSI)^2} \tag{37}$$

The mean square error between the weighted RSSI (WRSSI) and proposed RSSI (PRSSI) is calculated as follows:

$$MSE2 = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(PRSSI - WRSSI)^2} \tag{38}$$

The mean square error between the predicted RSSI (PrRSSI) and proposed RSSI (PRSSI) is calculated as follows:

$$MSE3 = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(PRSSI - PrRSSI)^2} \tag{39}$$

4. PROPOSED ALGORITHM

In this section, we present the proposed algorithm for distance based localization using Exponential Grey Prediction Model in WSN. The Step 1 to Step 7 we need to apply for the aforementioned task.

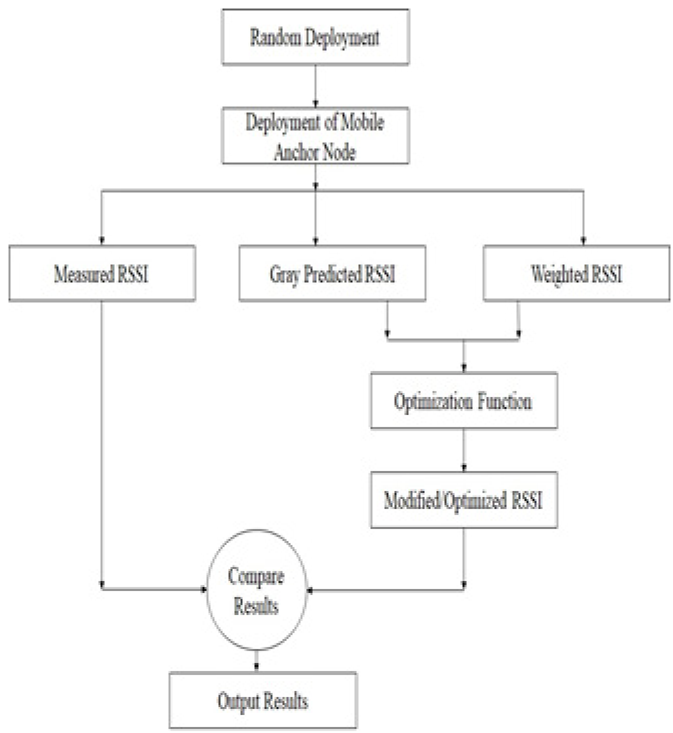
Step 1. Randomly deploy the normal sensor nodes with one anchor node.
Step 2. Collect the RSSI from all the nodes with respect to anchor node (Measured RSSI).
Step 3. Apply Exponential Grey prediction model to estimate the RSS value from all the nodes (Predicted RSSI)
Step 4. Apply the weight method to estimate the RSS value from all the nodes (Weighted RSSI)
Step 5. Combine the features from grey prediction and weighted grey prediction to estimate the optimized RSS value from all the sensor nodes by applying optimization function
Step 6. Calculate mean square error.
Step 7. Calculate the distance of all sensor nodes from the anchor node

The block diagram of the proposed system is shown in Figure 1. Initially the sensor nodes are deployed in the area of interest randomly. After the random deployment of the sensor nodes, the anchor node which is GPS enabled, is added in the network. The anchor node knows its position. The RSSI from the sensor nodes is measured at the anchor nodes as per its position. The RSSI measurement is done as per the Exponential Grey prediction model and is termed as predicted RSSI. The Weighted predicted RSSI are measured by applying some weights to the RSSI measurements.

The optimization function which uses predicted RSSI and Weighted predicted RSSI is then applied with some weighting factor as to calculate modified or optimized RSSI as explained in Equation (36). This optimization function combines the features of predicted RSSI using Exponential Grey prediction model and weighted predicted RSSI to estimate the new RSSI values. The Grey prediction model improve the prediction accuracy and the weighted prediction model balances the values by applying weights to the measured values to provide better results. The optimization function combines the prominent features from both the methods and provide efficient results. This modified RSSI is then compared with the measured RSSI to check its closeness and the accuracy of computation. The detailed experimentation results and the comparison are discussed in detail in section 5.

Grey prediction model is characterized by the exponential change in the raw data which changes with time. The whitenizating equation used in grey prediction is a linear differential equation which uses decreasing term (e^{-t}) to improve the predictive accuracy and also reduces the prediction error. The Exponential Grey prediction model is the modified version of earlier grey model where some parameters are added to deal with the abnormal changing in the given data.

Figure 1. Block diagram of the proposed system



The exponential grey prediction algorithm is used in predicting the future output value of the COVID19 cases in Turkey in the year 2020. This short-term forecasting model helped the government in changing the strategies for dealing with COVID19 pandemic situation according to the forecasting (Bilgil 2021).

5. RESULTS AND ANALYSIS

The MATLAB platform is utilized for the simulation and experimentations. Windows 10 operating system with Intel(R) Core(TM) i5-4310U CPU @ 2.00GHz, 2.60 GHz and 8 GB RAM is the configuration of machine considered for the experimentation. The coverage area considered for the experimentation is 100×100 meter and total 50 number of nodes are considered. The communication range of the sensors are utilized at its maximum level. Table 1 contains the values of RSSI with different methods and proposed approach.

The RSSI from all the sensor nodes is measured with respect to the anchor node. As the anchor node changes its position, the RSSI starts fluctuating. The predicted RSSI is calculated using Exponential Grey prediction algorithm. Figure 2 depicts the comparison of measured RSSI with the predicted RSSI and shows that the RSSI is fluctuating. Figure 3 compares the RSSI with respect to distance calculation for all the nodes with predicted values.

To reduce the fluctuation, the weighted predicted RSSI method is applied and compared with the original measured RSSI. Figure 4 shows the comparison between them. The fluctuation in RSSI values can be observed in the experimental results. Figure 5 shows the same with the distance calculation.

The optimized RSSI is calculated by applying the optimization function on the predicted RSSI and compared with the original measured RSSI. Figure 6 presents the comparison between the measured RSSI and optimized RSSI calculated using proposed approach. This optimized RSSI values against

Figure 2. Comparison of measured RSSI with predicted RSSI

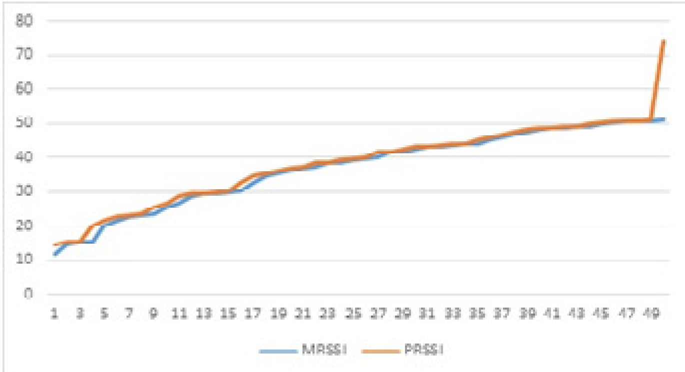


Table 1. RSSI measurements at the sensor nodes

Node ID	RSSI	PRSSI	WRSSI	PROPOSED	Node ID	RSSI	PRSSI	WRSSI	PROPOSED
1	-11.973031	-14.737491	-13.571606	**-12.57366747**	26	-39.593829	-40.145902	-39.878632	**-39.69085339**
2	-14.737491	-15.474794	-15.121771	**-14.86939889**	27	-40.145902	-41.524507	-40.889679	**-40.40823796**
3	-15.474794	-15.526628	-15.500789	**-15.48347637**	28	-41.524507	-41.83568	-41.68288	**-41.57794209**
4	-15.526628	-20.018248	-18.328939	**-16.67326588**	29	-41.83568	-42.622409	-42.246835	**-41.97710098**
5	-20.018248	-21.804329	-21.002467	**-20.37168981**	30	-42.622409	-43.040764	-42.836622	**-42.69499348**
6	-21.804329	-22.906794	-22.390451	**-22.00861944**	31	-43.040764	-43.377227	-43.212253	**-43.09868265**
7	-22.906794	-23.148466	-23.029311	**-22.94801811**	32	-43.377227	-43.784554	-43.585664	**-43.44782313**
8	-23.148466	-23.677826	-23.421206	**-23.24129591**	33	-43.784554	-44.009872	-43.898674	**-43.82292804**
9	-23.677826	-25.703701	-24.807835	**-24.08804259**	34	-44.009872	-44.152962	-44.082006	**-44.03405014**
10	-25.703701	-26.861609	-26.321131	**-25.91941289**	35	-44.152962	-45.354641	-44.795233	**-44.37777288**
11	-26.861609	-28.656168	-27.850928	**-27.21701773**	36	-45.354641	-45.879641	-45.625069	**-45.44666787**
12	-28.656168	-29.337162	-29.01	**-28.77734365**	37	-45.879641	-46.852852	-46.39345	**-46.05775096**
13	-29.337162	-29.663329	-29.503307	**-29.39325305**	38	-46.852852	-47.665568	-47.278193	**-46.99930979**
14	-29.663329	-29.990633	-29.830063	**-29.71962117**	39	-47.665568	-48.396329	-48.0463	**-47.79622244**
15	-29.990633	-30.459672	-30.231482	**-30.07240896**	40	-48.396329	-48.683275	-48.542171	**-48.44548903**
16	-30.459672	-32.537591	-31.621739	**-30.88252915**	41	-48.683275	-48.689074	-48.686175	**-48.68424208**
17	-32.537591	-34.496877	-33.626799	**-32.93180107**	42	-48.689074	-49.174441	-48.938534	**-48.77382954**
18	-34.496877	-35.29235	-34.912801	**-34.63999009**	43	-49.174441	-49.177398	-49.17592	**-49.17493392**
19	-35.29235	-36.121504	-35.726685	**-35.44200699**	44	-49.177398	-49.757153	-49.476942	**-49.27955901**
20	-36.121504	-37.006917	-36.586735	**-36.28218234**	45	-49.757153	-50.414121	-50.098048	**-49.87378308**
21	-37.006917	-37.516534	-37.269196	**-37.09611481**	46	-50.414121	-50.536722	-50.475854	**-50.43479626**
22	-37.516534	-38.394656	-37.977751	**-37.67577812**	47	-50.536722	-50.788147	-50.664253	**-50.57964973**
23	-38.394656	-38.646151	-38.522224	**-38.43759603**	48	-50.788147	-50.820472	-50.804339	**-50.79355097**
24	-38.646151	-39.296503	-38.983489	**-38.76153348**	49	-50.820472	-51.117733	-50.971645	**-50.87144995**
25	-39.296503	-39.593829	-39.44771	**-39.34749231**	50	-51.117733	-74.272795	-71.283447	**-66.59504705**

Figure 3. Distance measurement comparison corresponding to predicted RSSI (-db)

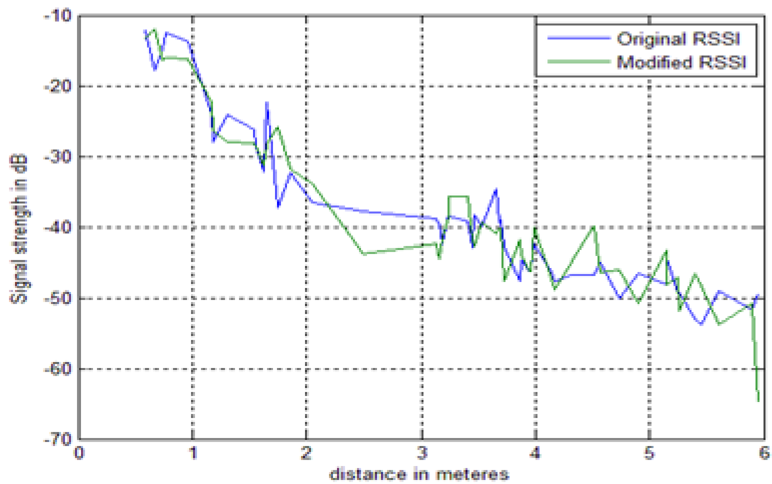
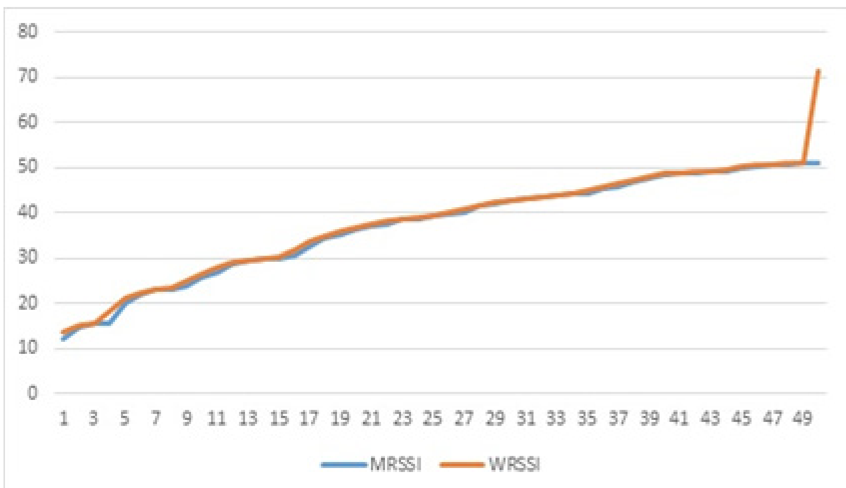


Figure 4. Comparison of measured RSSI with weighted RSSI



the distance calculation are shown in Figure 7. It is observed that the RSSI calculated using proposed algorithm generates almost same RSSI values as that of original RSSI and are stable. In addition, comparison of all the RSSI calculation with the proposed approach is presented in Figure 8 and the same in the context of distance for the estimated optimized RSSI is shown in Figure 9.

The comparison of mean square error (MSE) among different approaches is presented in the Table 2. Moreover, same has been shown in Figure 10. The different approaches have been proposed and have used different techniques for estimation. These techniques vary in the environment and the scope. Some techniques are identified with similar environment and scope and compared for their performance on selected parameters. Here, we can observe that the proposed algorithm achieves significantly better results as compared to other approaches as far as the error in the estimation is concerned. In addition, the obtained results are close to the original RSSI.

Figure 5. Distance measurement comparison corresponding to weighted predicted RSSI (-db)

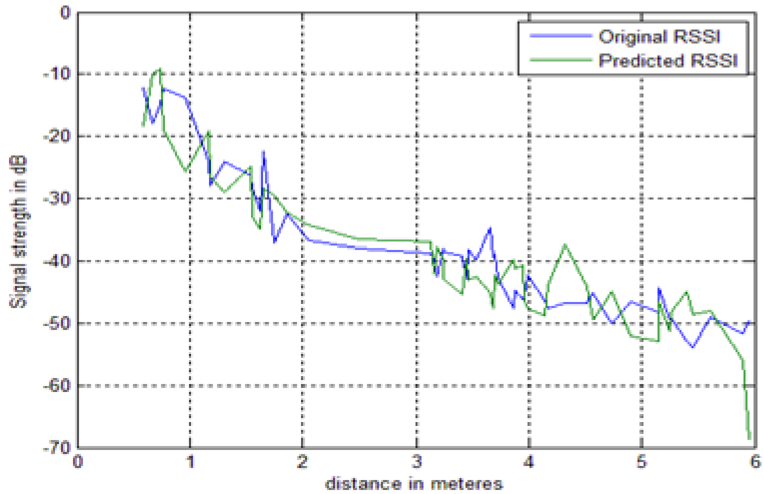
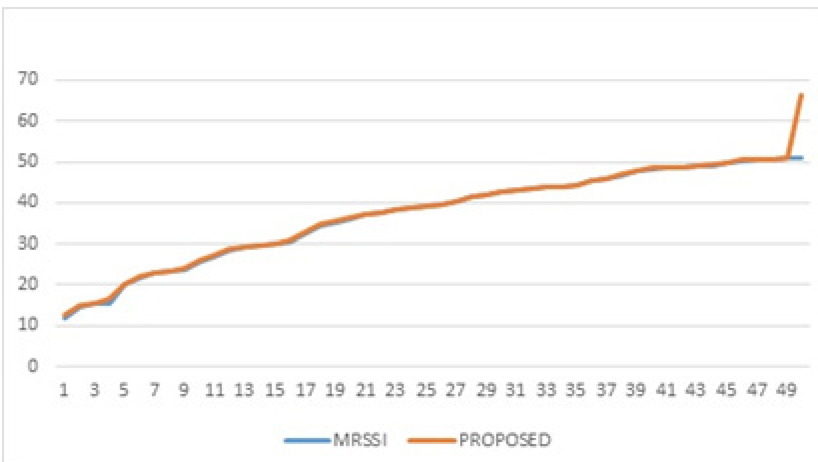


Figure 6. Comparison of measured RSSI with proposed RSSI



The distances of the sensor nodes are calculated from the anchor node by the RSSI calculated from all the methods and compared. Figure 11 to Figure 16 shows the distance calculation and the comparison of calculated distance. As shown in Figure 11, the distance is reducing exponentially with the increase in strength of RSSI values. Figure 12 shows the comparison of measured RSSI with the predicted RSSI. The comparison between the weighted predicted and the measured RSSI values is shown in Figure 13. The RSSI predicted using proposed algorithm and the measured RSSI is compared in Figure 14. From the analysis of the graph, it can be concluded that the proposed algorithm is providing closer values of RSSI to the measured RSSI values. The accuracy of prediction is better in weighted prediction method and more accurate in the proposed method. Figure 15 presents the distance comparison calculated by all the methods. The mean square error comparison by all the methods with the individual RSSI calculation is shown in Figure 16.

Figure 7. Distance measurement comparison corresponding to proposed RSSI (-db)

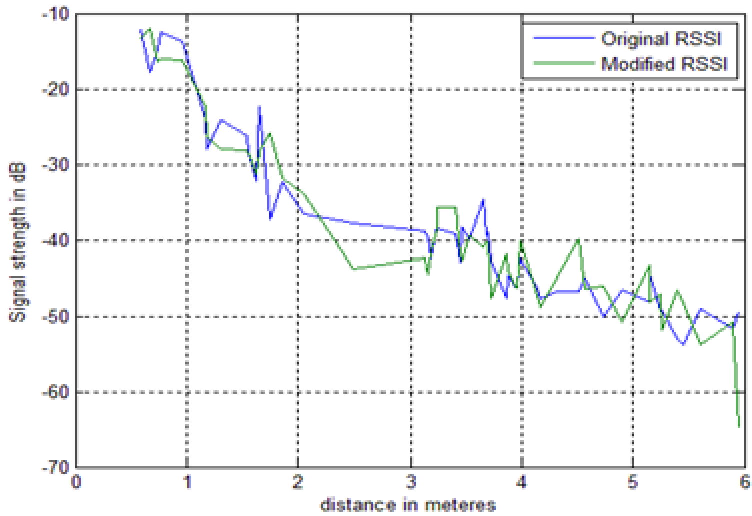
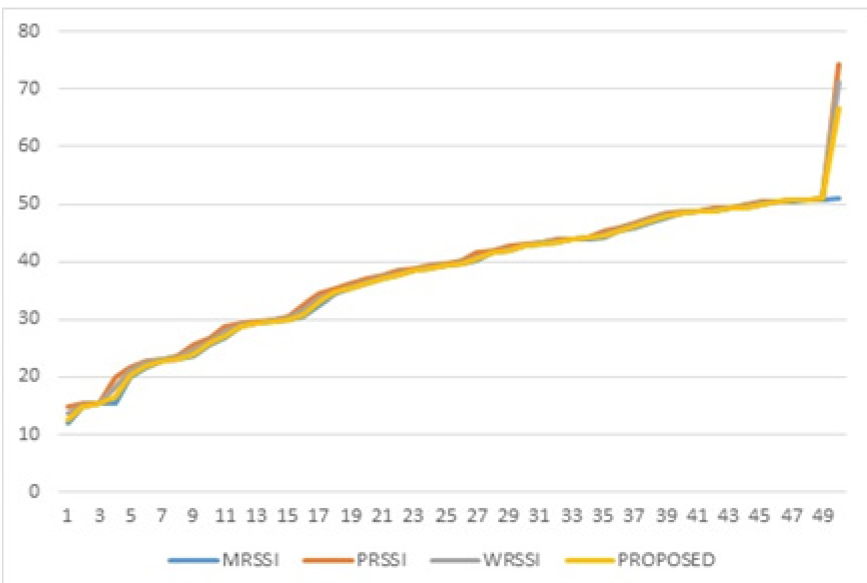


Figure 8. Comparison of all methods



6. CONCLUSION

This paper uses Exponential Grey prediction model for estimating the RSSI values from the sensor nodes to the anchor nodes. The Exponential Grey prediction model estimates the RSSI with reduced error. The Exponential Grey prediction model has an advantage of to be applied on larger sample space and its applicability in real time scenarios. These estimated RSSI values are then optimized using proposed objective function which offers more accurate and nearer values to the measured RSSI. The Grey predicted values and the weighted predicted values of RSSI used in optimization function

Figure 9. RSSI vs distance measurement comparison for all methods

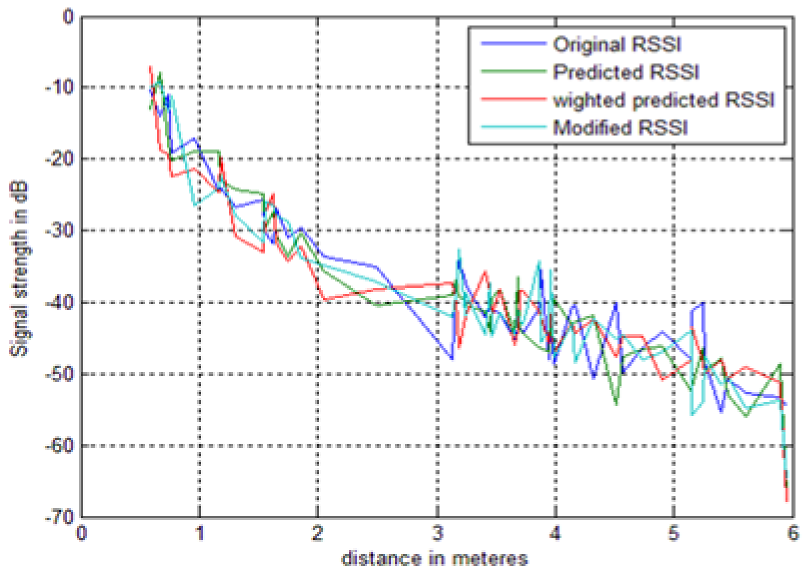
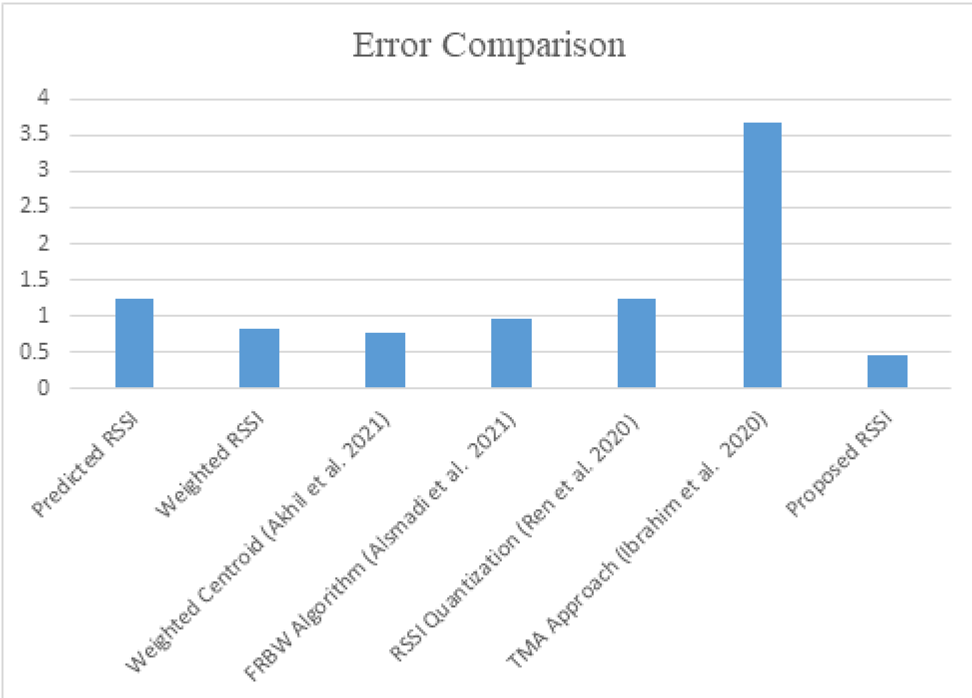


Table 2. MSE computation values

Methods	Mean Square Error (MSE)
Predicted RSSI	1.245995
Weighted RSSI	0.83042
Weighted Centroid Method [17]	0.78
FRBW Algorithm [18]	0.965714
RSSI Quantization [22]	1.23
TMA Approach [23]	3.66
Proposed RSSI	**0.46292**

proved to be efficient and obtained more accurate and nearer values to the measured RSSI. The mean square error is utilized for comparing the performance of the proposed approach with the conventional methods like weighted centroid method, RSSI quantization, TMA and FRBW algorithm. The results obtained from the proposed algorithm are compared with the Grey predicted RSSI and weighted predicted RSSI in terms of distance calculation with the measured RSSI. The comparison shows the significant improvement in the accuracy of the distance calculation by the proposed algorithm. The error comparison shows the proposed approach is efficient in estimating the distance from the anchor node more accurately. With the optimized RSSI values computed using proposed objective function, the sensor node can be accurately located. Moreover, any suitable location identification method can be applied to find the location of the sensor node. In future, the work can be extended for the partitioned network to study the feasibility of the proposed optimization function.

Figure 10. Comparison of estimation error



DECLARATIONS

Ethical Approval

Figure 11. Distance calculation

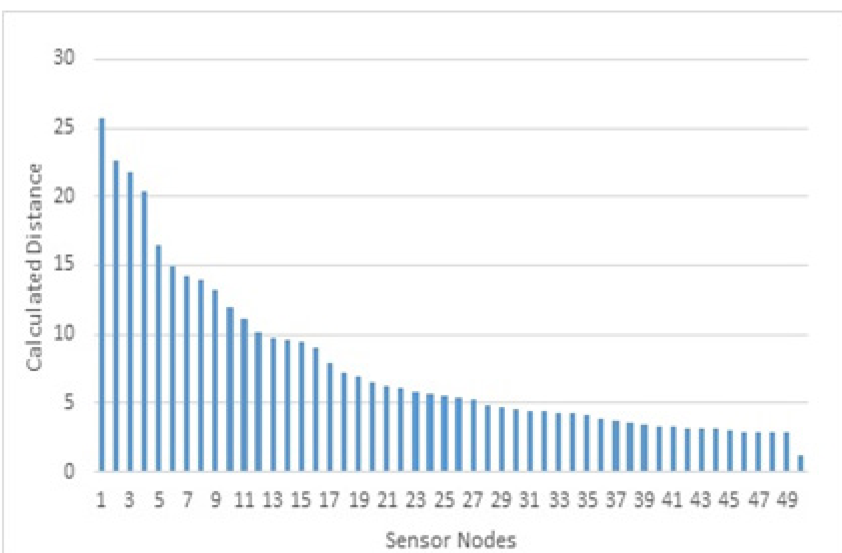


Figure 12. Distance comparison (MRSSI and PRSSI)

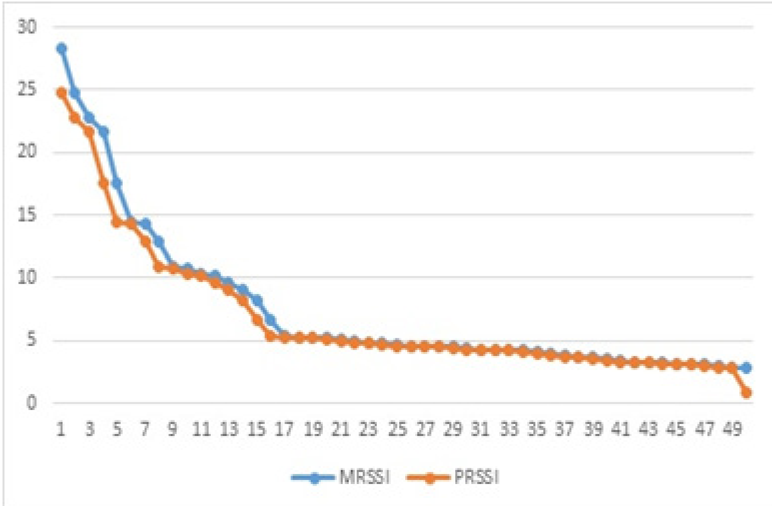
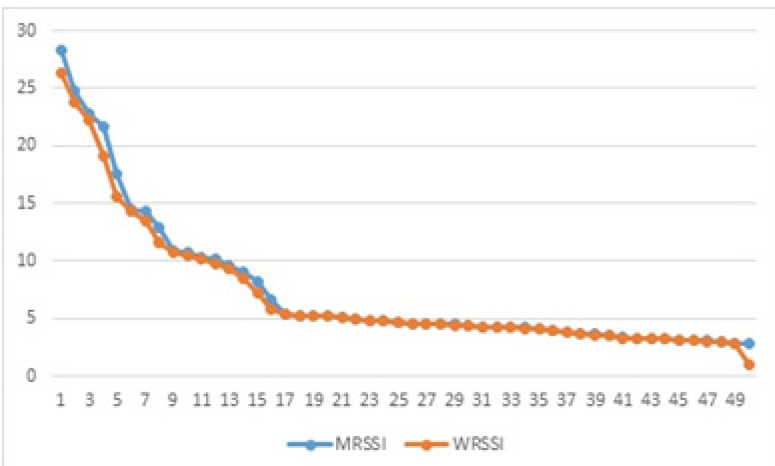


Figure 13. Distance comparison (MRSSI and WRSSI)



The authors declare that the work is original research that has not been published before.

Competing Interests

The authors declare that they have no competing interests.

Authors' Contributions.

Design, development and experimentation are performed by Dipak W. Wajgi and conceptualization, manuscript preparation, and revision are performed by Jitendra Tembhurne and Rakhi Wajgi

Funding

No funding

Figure 14. Distance comparison (MRSSI and proposed)

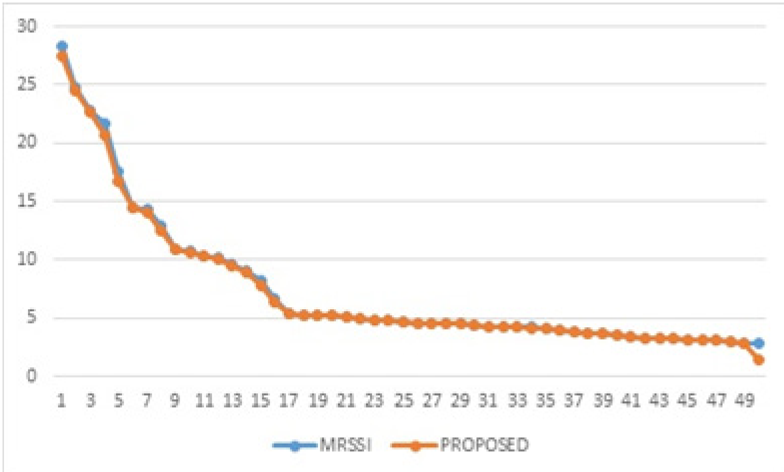
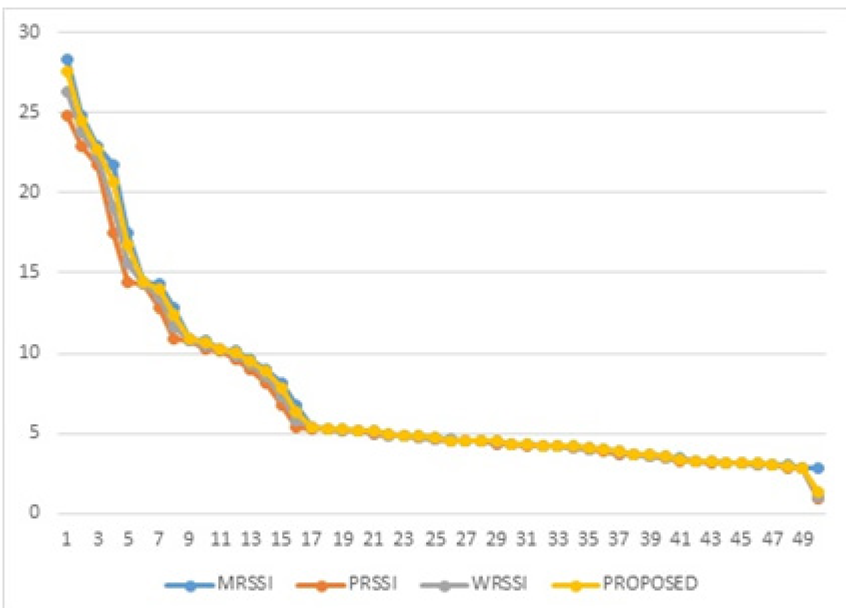


Figure 15. Distance comparison all methods



Data Availability

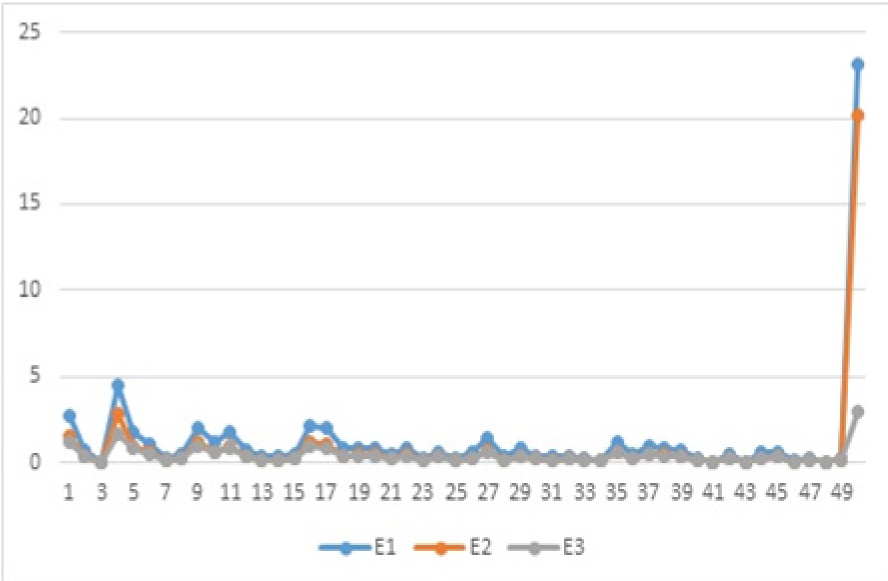
The information about the data source is provided

Processing Dates

08, 2024

This manuscript was initially received for consideration for the journal on 08/07/2022, revisions were received for the manuscript following the double-anonymized peer review on 08/01/2024, the

Figure 16. Error comparison



manuscript was formally accepted on 07/31/2024, and the manuscript was finalized for publication on 08/08/2024

Corresponding Author

Correspondence should be addressed to Dipak Wajgi; dipak.wajgi@gmail.com

REFERENCES

Akhil, K. M., Seethalakshmi, K., & Sinha, S. (2021, May). RSSI Based Positioning System for WSN with improved Accuracy. In 2021 3rd International Conference on Signal Processing and Communication (ICPSC) (pp. 325-329). IEEE. DOI:10.1109/ICSPC51351.2021.9451801

Alavijeh, A. K., Ramezani, M. H., & Alavijeh, A. K. (2018). Localization improvement in wireless sensor networks using a new statistical channel model. *Sensors and Actuators. A, Physical*, *271*, 283–289. DOI:10.1016/j.sna.2018.01.015

Alsmadi, L., Kong, X., Sandrasegaran, K., & Fang, G. (2021). An Improved Indoor Positioning Accuracy using Filtered RSSI and Beacon Weight. *IEEE Sensors Journal*, *21*(16), 18205–18213. Advance online publication. DOI:10.1109/JSEN.2021.3085323

Bal, M., Liu, M., Shen, W., & Ghenniwa, H. (2009, April). Localization in cooperative wireless sensor networks: A review. In 2009 13th International Conference on Computer Supported Cooperative Work in Design (pp. 438-443). IEEE. DOI:10.1109/CSCWD.2009.4968098

Baloochian, H., & Balochian, S. (2020). Improving Grey Prediction Model and Its Application in Predicting the Number of Users of a Public Road Transportation System. *Journal of Intelligent Systems*, *30*(1), 104–114. Advance online publication. DOI:10.1515/jisys-2019-0082

Bilgil, H. (2021). New grey forecasting model with its application and computer code. *AIMS Mathematics*, *6*(2), 1497–1514. DOI:10.3934/math.2021091

Chuku, N., & Nasipuri, A. (2021). RSSI-Based localization schemes for wireless sensor networks using outlier detection. *Journal of Sensor and Actuator Networks*, *10*(1), 10. DOI:10.3390/jsan10010010

Elayan, H., & Shubair, R. M. (2018). Towards an Intelligent Deployment of Wireless Sensor Networks. In *Information Innovation Technology in Smart Cities* (pp. 235–250). Springer., DOI:10.1007/978-981-10-1741-4_16

Flammini, A., Marioli, D., Mazzoleni, G., Sisinni, E., & Taroni, A. (2006, April). Received signal strength characterization for wireless sensor networking. In *2006 IEEE Instrumentation and Measurement Technology Conference Proceedings* (pp. 207-211). IEEE. DOI:10.1109/IMTC.2006.328372

Ibrahim, B. K.; Mahdi, M. A.; Salman, M. A. (2020, April). Triple Mobile Anchors Approach for Localization in WSN. In 2020 InternationalConference on Computer Science and Software Engineering (CSASE) (pp. 174-179). IEEE. DOI:10.1109/CSASE48920.2020.9142084

Jain, C., Sashank, G. V. S., & Markkandan, S. (2021, March). Low-cost BLE based Indoor Localization using RSSI Fingerprinting and Machine Learning. In *2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)* (pp. 363-367). IEEE. DOI:10.1109/WiSPNET51692.2021.9419388

Li, G., Geng, E., Ye, Z., Xu, Y., Lin, J., & Pang, Y. (2018). Indoor positioning algorithm based on the improved RSSI distance model. *Sensors (Basel)*, *18*(9), 2820. DOI:10.3390/s18092820 PMID:30150521

Pal, A. (2010). Localization algorithms in wireless sensor networks: Current approaches and future challenges. *Netw. Protoc. Algorithms*, *2*(1), 45–73. DOI:10.5296/npa.v2i1.279

Paul, A. K.; Sato, T. (2017). Localization in wireless sensor networks: A survey on algorithms, measurement techniques, applications and challenges. Journal of sensor and actuator networks, 6(4), 24. DOI:10.3390/jsan6040024

Rashid, H., & Turuk, A. K. (2013). Localization of wireless sensor networks using a single anchor node. *Wireless Personal Communications*, *72*(2), 975–986. DOI:10.1007/s11277-013-1050-y

Ren, Q., Zhang, Y., Nikolaidis, I., Li, J., & Pan, Y. (2020). RSSI quantization and genetic algorithm based localization in wireless sensor networks. *Ad Hoc Networks*, *107*, 102255. DOI:10.1016/j.adhoc.2020.102255

Sharma, G., Kumar, A., Singh, P., & Hafeez, M. J. (2018). Localization in wireless sensor networks using invasive weed optimization based on fuzzy logic system. In *Advanced Computing and Communication Technologies* (pp. 245–255). Springer. DOI:10.1007/978-981-10-4603-2_23

Tomic, S., Beko, M., Dinis, R., & Montezuma, P. (2017). Distributed algorithm for target localization in wireless sensor networks using RSS and AoA measurements. *Pervasive and Mobile Computing*, *37*, 63–77. DOI:10.1016/j.pmcj.2016.09.013

Xia, M., Zhang, X., & Zhu, Y. (2019). Real time localization algorithm based on local linear embedding optimization in sensor networks. *Cluster Computing*, *22*(2), 4173–4178. DOI:10.1007/s10586-018-1697-y

Xu, K., Chen, M., & Liu, Y. (2008, August). A novel localization algorithm based on received signal strength indicator for wireless sensor networks. In *2008 International Conference on Computer Science and Information Technology* (pp. 249-253). IEEE. DOI:10.1109/ICCSIT.2008.188

Xu, L., Yang, F., Jiang, Y., Zhang, L., Feng, C., & Bao, N. (2011, January). Variation of received signal strength in wireless sensor network. In 2011 3rd International Conference on Advanced Computer Control (pp. 151-154). IEEE. DOI:10.1109/ICACC.2011.6016387

Yaghoubi, F., Abbasfar, A. A., & Maham, B. (2014). Energy-efficient RSSI-based localization for wireless sensor networks. *IEEE Communications Letters*, *18*(6), 973–976. DOI:10.1109/LCOMM.2014.2320939

Yin, Y., Wang, Q., Zhang, H., & Xu, H. (2021). A Novel Distributed Sensor Fusion Algorithm for RSSI-Based Location Estimation Using the Unscented Kalman Filter. *Wireless Personal Communications*, *117*(2), 607–621. DOI:10.1007/s11277-020-07888-w

Yun, S., Lee, J., Chung, W., Kim, E., & Kim, S. (2009). A soft computing approach to localization in wireless sensor networks. *Expert Systems with Applications*, *36*(4), 7552–7561. DOI:10.1016/j.eswa.2008.09.064

Dr. Dipak W. Wajgi has completed his B.E in Computer Technology from KITS, Ramtek and M.Tech. from RCOEM, Nagpur. He has done his Ph.D. in computer science and engineering from Indian Institute of Information Technology, Nagpur. He has over twenty three international publication on his name.

Dr. Jitendra V. Tembhurne has completed his Ph.D. from VNIT, Nagpur. Currently he is working as an Assistant Professor in Indian Institute of Information technology, Nagpur. He has over fifty international publications on his name.

Dr. Rakhi Wajgi has completed her Ph.D. from RTMNU, Nagpur university. She has done her M.Tech. from BITS, Pilani. She has over twenty five international publication on her name.