

Integration of Sensing Holes and Energy Depletion with Time Windows in Wireless Sensor Networks

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Abstract

Adapting sensor nodes to suit their specific sensing and communication capabilities can pose challenges, especially in harsh environments. Therefore, finding an optimal solution heavily depends on the deployment context. In this study, we aim to eliminate blind spots by considering the trade-offs between power consumption and sensor coverage among consecutive nodes. We calculate and monitor the relationship between the available power and the area that sensors can effectively cover over a defined time frame. Additionally, we investigate a pair of sensors with specific characteristics related to their remaining energy and sensing range. To analyze the data, logistic regression is employed, taking into account the aspects of residual energy and the communication capabilities of these sensors.

1 Introduction

Customizing sensor nodes with appropriate sensing and communication capacity, bound to cause problems in hostile environments. The influence of transmission power on wireless sensors indices such as outage probability and its productivity (eg throughput and packet delivery) is stated with attacker trying to overplay with its computing power levels. So if any area coverage is not provided intruders easily capture the sensing field.

The conservation of energy aspect either at wireless sensor node level, network level provide long functionality. The emphasis in this work had been based on network level with reporting data to sink. Amplifying coverage radii of certain nodes without reposition based on covered event had been done.

2 Prior works on sensing power, security threats in wireless sensor networks

The coverage protocol classifications based on frequency in monitoring is “point”, “area” and “barrier” coverage. Sensing model based on connectivity is “connectivity aware” and unaware connectivity. Classification based on ability of sensing as “deterministic” or “probability based” [7].

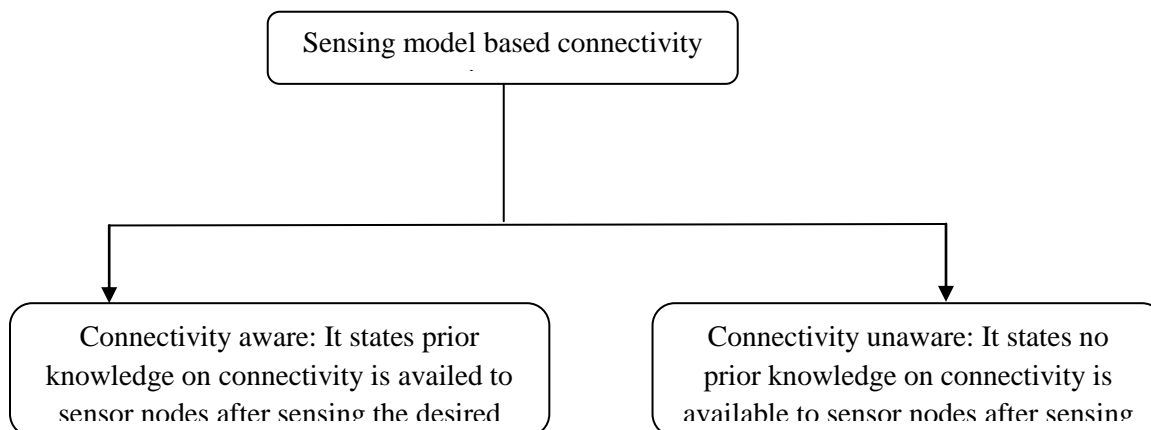


Figure1 Sensing model based connectivity issues.

Every sensor has a communication range which depends on the ability to connect to nearby sensor. In scenario of non-availability in sensors or sink in sensing field is available to a sensor node then a connectivity unaware situation occurs. Sensing and communication awareness in a sensing field is shown in figure1.

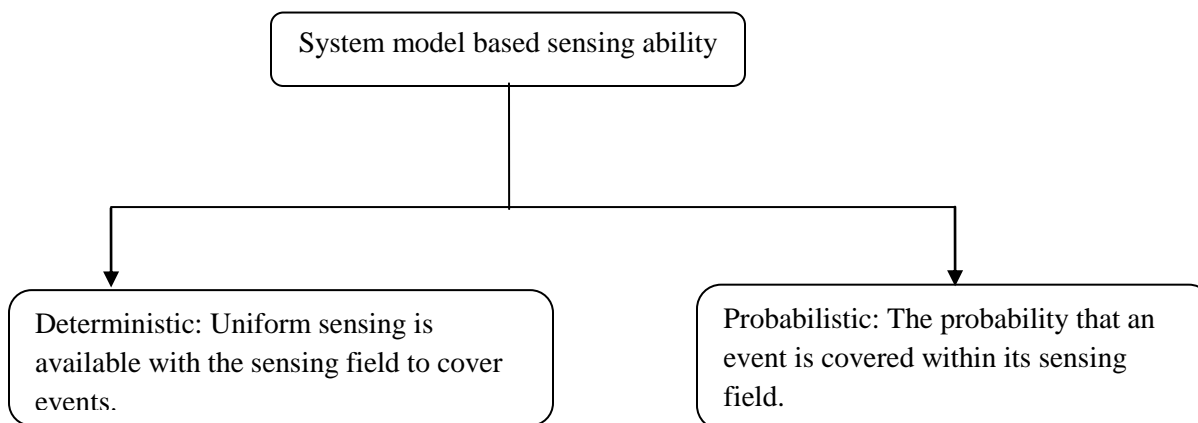


Figure2 Sensing ability based classification in wsn.

The sensing ability based taxonomy is shown in figure2 involved in wireless sensor nodes [7]. Activated sensors with trade off in levels of coverage had been studied using topological method. Activator nodes deployed in the topology ensures coverage quality by activating specific sensors. The characteristics of computing maximal separation distance between them in sensing and assigning decay factor provides for long network lifetime [8].

2.1 Security issues and graph theory procedures in wireless sensor nodes

Physical layer security issue in wireless sensor nodes, with channel state information and its outage probability with secrecy rate of event (eavesdropping) had been discussed with small scale fading model. The solutions states that estimating the degradation levels and assigning proper scheduling improves the channel realization characteristics [1]. The, reciprocal channel state at sink facilitates the estimation of increased signal to noise ratio improving its security measures. In [2], transmission routes and analysing its outage probability with decision variant algorithm (Steiner algorithm) had been studied. The geometrical constrains of heterogeneous nodes in communication graph and its conductive process to associate to various vertices at minimal time is provides by assigning suitable weights.

Identifying malicious nodes with time, geographical coordinates and correlation of events had been studied inconsistency in event judgement of sensors with faulty data. The total traffic is a sum of real data along with faulty data. Posterior estimation with time series (ARIMA) and its error calculations overcomes the finding in temporal judgement of malicious activity. Proximity of node degree with reliability value of trust provides spatial evaluation in judgement of faulty data [3]. Depending on the available power of wireless sensor node the study in [4], states “regular function” it sends single measurement in a time epoch thereby fulfilling its operations. On the counter part if there is reduced function in power it sends measurement in lengthening time epoch causing insufficient reporting. In [5] the lifetime of sensor node is discussed with associated point coverage model and bat algorithm. The sensing field had been divided into sub-terrains

when estimating dying nodes blatant priority value changes the role of active sensors. Thus gradual death of sensors happens whereby adding energy prolongs lasting operations.

3. Problem statement

Identifying the coverage holes purpose is to find the extent of the missing coverage in the sensing field. The resource of power available in sensors deployed in the nearby proximity of missing coverage area is to be estimated in shorter time span. This work assumes that wireless sensor node had reduced functionality with minimizing its sensing area as power constrains occurs. Node level residual energy calculations of individual sensor involved in sensing might mitigate the problem of elapsed coverage in shorter duration. Hence, analysing this awareness among nodes had to be achieved.

4. Overview of the proposed work

The barriers between power consumption and sensing coverage with successive nodes are set for a reassuring lack of blind spots. A relationship between available power and the sensing area is calculated and observed over a specific time window. A single pair of sensors with device-oriented features of residual energy and sensing in terms of distance has been explored.

In this work the pairing of nodes provide the redundancy in covering an event. Logistic regression had been used to analyse the outcome probability between 0 and 1. A brief overview of the protocol is shown in table 1.

Protocol	Network and protocol	Problem	Solutions and
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Name	background	Addressed	Results Inferred
Pairwise Data Transfer Through Wireless Sensor Sensing and Communication	Virtual coordinates where assigned to deployed sensors. Subsequently, event occurrence with missing time epoch due to power depletion has been observed.	Identifying missing events due to power depletion within a time window and estimating the residual energy of pairwise nodes in its deployed coordinates.	Collocated sensors within the deployed scenario and its capability of sensing where estimated with logistic regression approach.

Table 1 PWWSSCDT overview of the protocol.

A pairwise wireless sensor nodes feature is developed with two collocated nodes in terrain. A counter fit measure where the blind spots are systematically estimated via power and distance relationship is examined incorporating logistic regression.

4.1 Algorithm Implementation

Modifying the range of the co-located sensor node to guarantee monitoring of the sensing field through pairwise sensing, equation 1 has been employed to represent the entire high-dimensional space.

$$\{X_i\}_{i=1}^N \quad (1)$$

Compute the discriminative unsupervised learning function using logistic regression, as described in equation 2. In this equation, "m" represents the slope, "a" stands for the sensory data points, and "c" represents the intercept.

$$y = ma + c \quad (2)$$

Collocated sensors are employed to detect linearly separable sensing points, with the sink positioned as the vertex. This setup distinguishes between positive (+1) and negative (-1) points. The weight updating process between individual sensors is detailed in equation 3.

$$y = w^t a_i \quad (3)$$

The accuracy of classification is quantified by equation 4 for correct classifications and equation 5 for misclassifications.

$$y \times w^t a > 0 \quad (4)$$

$$y \times w^t a < 0 \quad (5)$$

The equation representing the best fit line is given as equation 6. To remove outliers, the "Sigmoid" function (f) is employed.

$$\max f \sum_{i=1}^n f(y_i \times w^t a_i) \quad (6)$$

The value of "f" is given as in equation

$$f = \frac{1}{1+e^{-c}}$$

The "c" value is given by equation 6 (b)

$$c = y_i \times w^t a_i \quad (\text{Equation 6 b})$$

Thus the sensing sub area is estimated via logistic regression as a discriminative set of covered and blind spot areas.

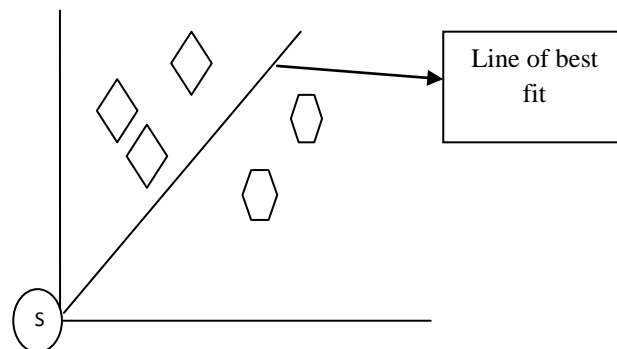


Figure3 Topological assessments as a function of coverage and distance to sink.

4.2Pair Wise Wireless Sensors based Sensing and Communication with Data Transfer (PWWSSCDT)

In Figure 3, the sink, denoted as 's,' is centrally located, and the associated sensors are categorized based on their sensing as the dependent variable and their distance as the

independent variable. To initiate the process, all sensors are initialized and their sensing areas are defined. The total power (TP) in Watts required to cover a sensing area is then converted to dBm. If the total power of the sensors falls below a desired threshold, the classification is performed based on equation 4 for correct classifications and equation 5 for misclassifications. In the case of exact classification, a value of 1 is reported, indicating that the sensor can cover the desired area within the specified time window. However, in the case of misclassification, a value of 0 is reported, indicating that the sensor cannot cover the desired area within the time window.

In the event of misclassification, the residual energy of 5 sensors is estimated, and additional coverage is assigned within the same time window. This is achieved by converting the total power of collocated sensors into sensing subareas within the depleted sensor terrain. Finally, a numerical model is employed, utilizing a logistic regression model, to determine the likelihood of "event occurrence" while considering the impact of the time window and total power.

5 Results of Simulation works

Simulation assessment of the protocol is established with MATLAB using the table 2 below.

Simulation assessment Parameter	Value
Simulation area	500 m ×500 m
Transmission power	2.5W
Reception power	0.20 W
Initial energy	4 J
Number of sink	1
Simulation duration	600s

Table 2 Simulation assessment parameters and its values used for PWWSSCDT.

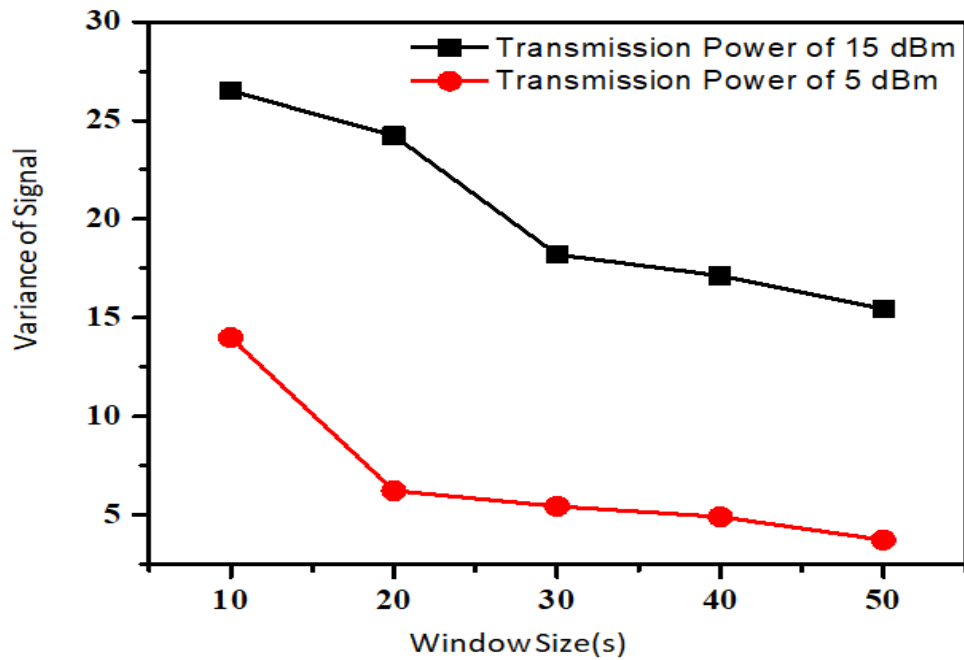


Figure4 Variance of signal versus time window size.

Figure 4 illustrates the relationship between signal window duration and transmission power to communication distance in dBm. Meanwhile, in Figure 5, the estimation of residual energy for collocated sensors is carried out through the exchange of control packets within the same window size.

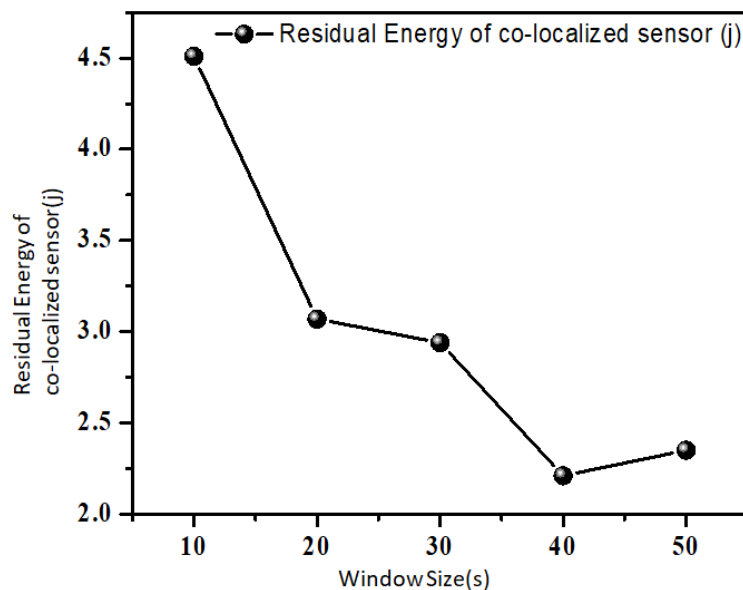


Figure 5, Residual Energy of collocated sensor versus time window size.

In Figure 5, the residual energy of a single collocated sensor is estimated, taking advantage of the relationship in its residual energy characteristics.

5.1 Statistical validations

Data interpretation using “Bluesky statistics tool for interpreting the characteristic of residual is done as shown in figure4 to figure5 The context of numerical values obtained is shown as in table 3 via MATLAB simulator.

Residual Energy of co-localized sensor-2 (J)	Window size (s)	Variance of signal sensor-1	Coverage Event occurrence (COE)
		Transmission power 5 dBm	
4.51	10	14	1
3.07	20	6.24	1
2.94	30	5.45	0
2.21	40	4.92	0
2.35	50	3.75	0

Table 3 Shows numerical values obtained with MATLAB simulation.

The work coverage is characterized by deployment density of sensors. In scenario of co-localized sensors deployed with predetermined sensing radius captures events as long as it retains the energy involved in sensing. As simulation progress the initial energy diminishes to extent where in ability to capture events is missing and termed as 0 and which captures the event is termed as 1.

Residual Standard Error	Df	F statistic	P value
0.5077	3	1.6552	0.2885

Table 4 F-statistic for scenario 1.

The residual standard error and F statistics is shown in table 4. The p value is not significant as a very small sample size. However the residual error indicates trustworthy nature of data.

Minimum	First Quartile	Median	Third Quartile	Maximum
-0.4605	-0.3128	-0.1603	0.4365	0.4972

Table 5 Residuals for scenario 1

The residuals in table 5 indicate the actual data points and difference data point predicted by the model. The minimum, medium, maximum and its quartile for scenario 1 data are shown.

Sum of squares table	
Sum of squares of Regression	0.4267
Sum of squares of Residual	0.7733
Total sum of squares	1.2

Table 6 Sum of squares table for regression model is scenario 1.

In table the total sum of squares in regression had been shown with linear regression as in table 6.

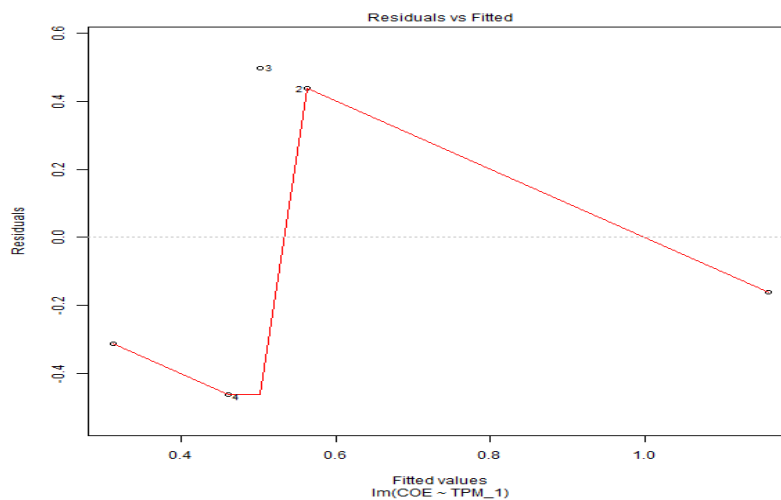
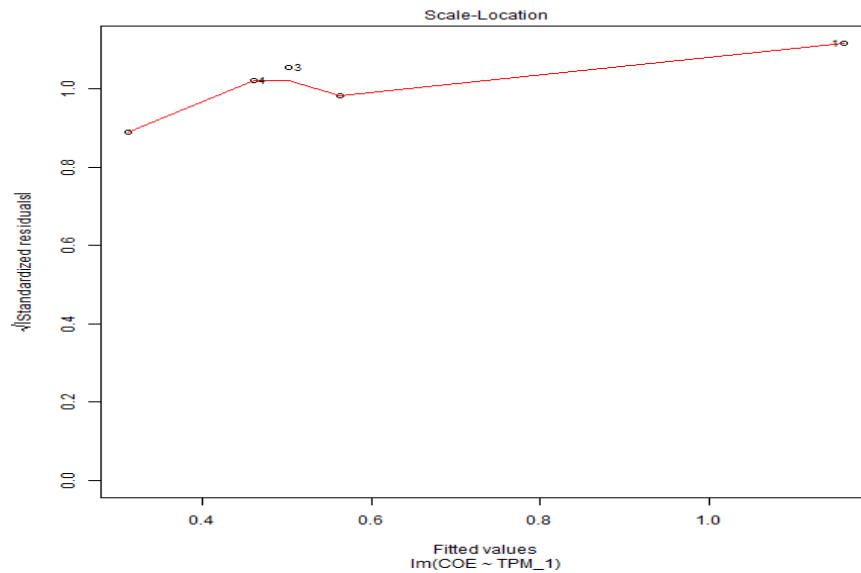


Figure6 Residual versus fitted model for PWWSSCDT data in scenario 1.

In Figure 6, the residual fit for COE (Coefficient of Expansion) versus Transmission power at 5 dBm is displayed. The data points are labeled, with the response strength being represented on the y-axis (residuals) and the fitted values on the x-axis.

**Figure7 Standard deviation of Residual versus fitted values.**

In figure7, standardized residual is plotted in y axis with the fitted values in x axis.

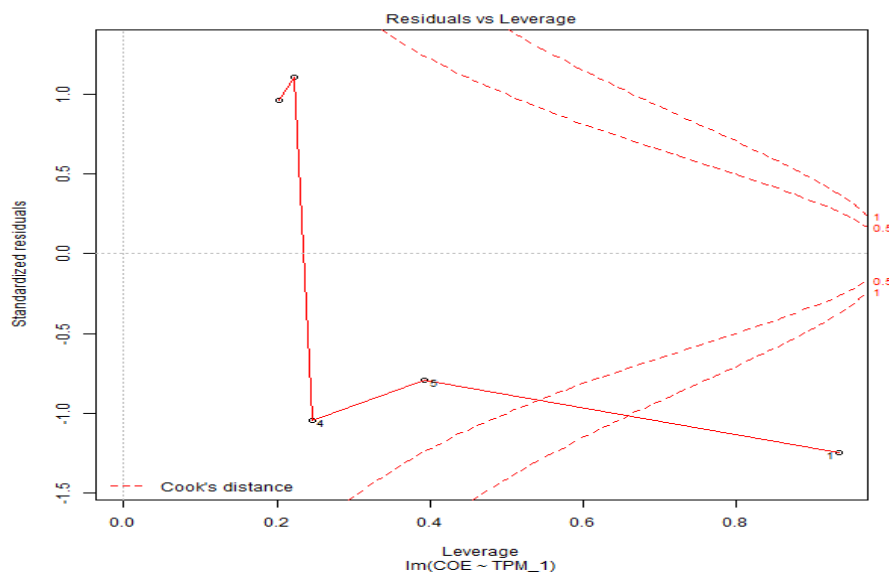


Figure 8 displays the standard residuals for COE versus Transmission power at 5 dBm, along with Cook's distance.

Cook's distance is utilized to identify influential outliers that have a negative impact on the results obtained in the regression analysis, as shown in Figure 8.

Scenario two is shown below.

Residual Energy of co- localized sensor-2 (J)	Window size (s)	Variance of signal sensor-2	Coverage Event occurrence (COE)
		Transmission power 15 dBm	
4.41	10	26.5	1
4.02	20	24.23	1
3.23	30	18.21	0
2.91	40	17.13	0
2.56	50	15.45	0

Table 7 Shows numerical values obtained with MATLAB simulation.

In table 8 shows the residual energy of sensor is low when compared to 6.2 as more transmission power is utilized in transmitting data as a function of distance. Subsequently, the adverse impact of coverage is less.

A regression analysis with transmission power as independent variable and coverage of event as dependant variable is developed.

Residual Standard Error	Df	F statistic	P value
0.328	3	8.1522	0.0648

Table 8 F-statistic for scenario 2.

Residual standard error in table 8 indicates the scenario is better compared to the prior scenario 1 in table 4.

Minimum	First Quartile	Median	Third Quartile	Maximum
-0.3123	-0.1368	-0.1018	0.1263	0.4246

Table 9 Residuals for scenario 2.

Residual are shown in table 10 with first and third quartile along with minimum to maximum values and its median.

Sum of squares table	
Sum of squares of Regression	0.8772
Sum of squares of Residual	0.3228
Total sum of squares	1.2

Table 10 Sum of squares table for regression model is scenario 2.

In table the total sum of squares in regression had been shown with linear regression as in table 11.

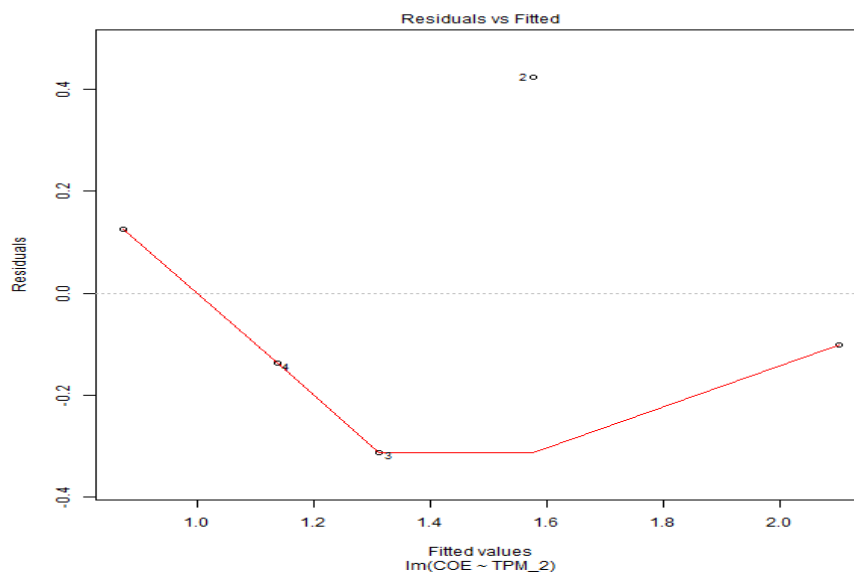


Figure9 Residual versus fitted value for scenario 2.

In figure9 the pattern shows the fitted model is a good fit since the pattern is detectable.

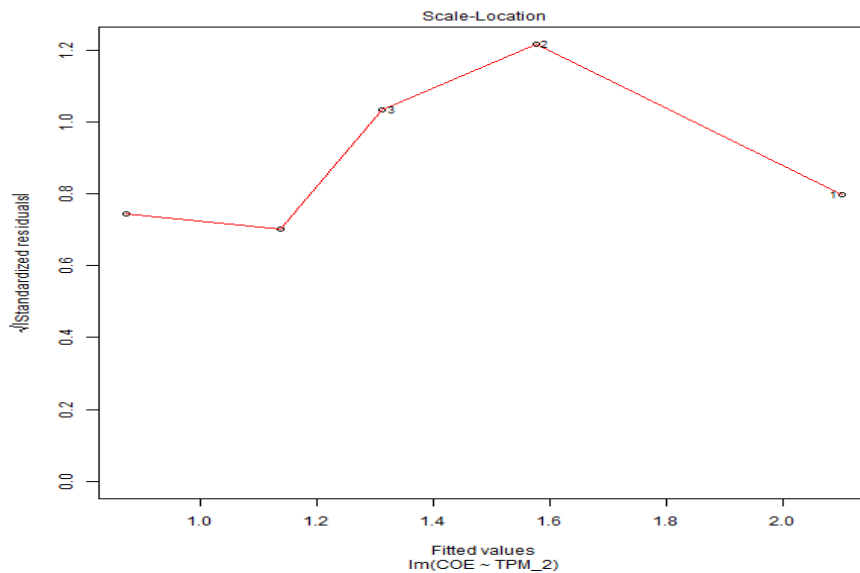


Figure 10 Standardized residual versus fitted value for scenario 2.

A standard score is provided and the residuals are potted in figure10 with its fitted values for scenario 2.

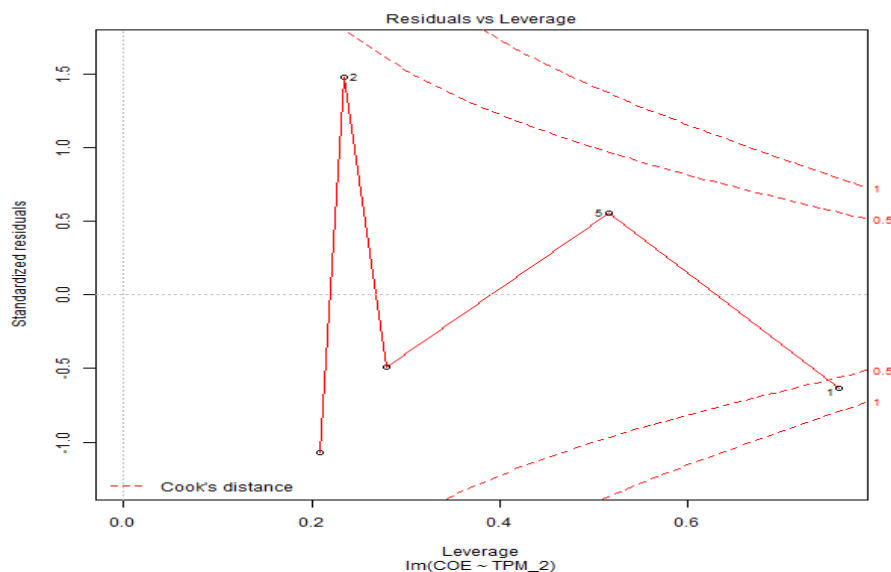


Figure11 Standard residual for COE versus Transmission power at 15 dBm with cook's distance.

The cook's distance is used for predicting the influential outliers that exhibits in the regression analysis obtained results under negative impact as in figure11.

6. Conclusion

Active sensing power sharing had been achieved in small granular time with the process of nodes energy knowledge within the topology. Assessment of simulation results indicates the superiority of ensuring sensing and assigning successive nodes for balancing its resources of energy. The collocated sensor pair using a probabilistic sensing model is deployed. Then the relationship between its sensed area and the total power of one sensor is estimated. Simultaneously, the energy behaviour of the proximity sensor and its counter to balance the sensing terrain is characterized. A logistic regression model has been used for this classification. Further, statistical analysis has been done with a generalised linear model to observe the fitness of data obtained for Pair wise Wireless Sensors-based Sensing and Communication with Data Transfer.

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