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A Real and Accurate Energy Efficient Localization Model in WSN Using Machine Learning Technique

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Abstract

The wireless sensor network is the key deciding element in communication, the 4G and 5G LTE communication models are offering many applications such as data accessing, and data rate controlling, multimedia and live streaming applications. Therefore, an advanced wireless sensor network designing and its development is compulsory to provide the above applications. The wireless sensor networks are dynamic in nature, so that they can change their behavior with little time. Due to time-variant action, internal and external factors cannot be predictable. WSN facing power constrains issue, node failure, and homogeneity node accessing and node scalability problems. Moreover WSN network challenging following key parameters such as the high bandwidth, high energy consumption, QOS, cross layer communication and physical channel. The lifespan of the sensor network, Maximum usage of resources and system are the main limitations

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of the earlier method. The existed architecture and optimization models cannot solve the above limitations and significant problems. In this research work addressing the machine learning-based WSN node localization technique, the node localization is a complex problem due to more number of elements to be estimated between sensor nodes. In this paper, node localization, objective function, mean-average error in localization, anchor node density and estimated position parameters are analyzed with various methodologies. At final proposed an advanced localization technique with machine learning model for future generations.

Keywords: WSN, node localization, sensor nodes, machine learning,Energy

1 Introduction

The accurate wireless sensor localization technique is challenging for current researchers. WSN applications such as defense, target detection, fire detection and military applications are the major issues facing by developing nations. The above applications are possible only with advanced WSN and its node localization (NL) mechanisms. The procedure of quantifying the physical location of deployed nodes in a WSN network is called as localization. An easy solution for this NL is to incorporating GPS(Global positioning system). It is providing the exact position of node coordination. But, this modeling is un-reliable and not a realistic technique due to more scalable nodes. The power consumption and environmental issues are more because of above method. So, that an alternative approach is to be identified for locating the position of nodes [1]. The centralized WSN network only estimated the nearest nodes and anchor nodes with a known position. Every WSN network consists of a large number of sensor nodes and these can perform many applications with accurate functioning. The localization of sensor nodes is necessary for improving the cost, low power, sensing capability, communication and computations [2]. The WSN networks are made with multiple sensors through tiny size. These are operated with fewer resources and low power conditions. But, less number of sensor nodes cannot handle the major applications with less time. So, a large number of sensor nodes and deployment is necessary. Sensor nodes are continuously collecting and sending information from the target region via an available environment. The sensing, collection of data and central units design is a major problem for processing the communication between the nodes. A Different sensor nodes are available such as thermal, optical, acoustic and weather-related; these are capable of offering many powerful applications. The WSN network is facing many issues such as data aggregation, information reliability, clustering, energy awaring, routing, localization, scheduling, fault detection and security. The above all issues are challenged by many researchers and developed efficient optimization technique. But, for localization, no accurate mechanism is available for solving the WSN functional complexity.

Table 1 Elements in Localization

S.No	Parameter Optimization	Existed Algorithm	Performance
1	M(unknown nodes)	GA, PSO, ABC	Accurate, moderate, average.
2	K(Anchor nodes)	bayesian	Low
3	B-PC	GA, bayesian	Good, Accurate
4	MD-PC	Bayesian	Moderate
5	Class-based localization	DT	Moderate
6	Main error	GA,DT	Good
7	Node density estimation	KNN, DT	Efficient
8	Non-linear soft localization	Neural networks	High
9	Target and source classification	SVM	Moderate
10	Distributive function	DT	High

Table 1 clearly explains various elements and its adjustment through earlier methods. In this, their performance is estimating over accurate, good moderate and low terms. This analysis is most useful for designing the best node localization mechanism for wireless sensor networks.

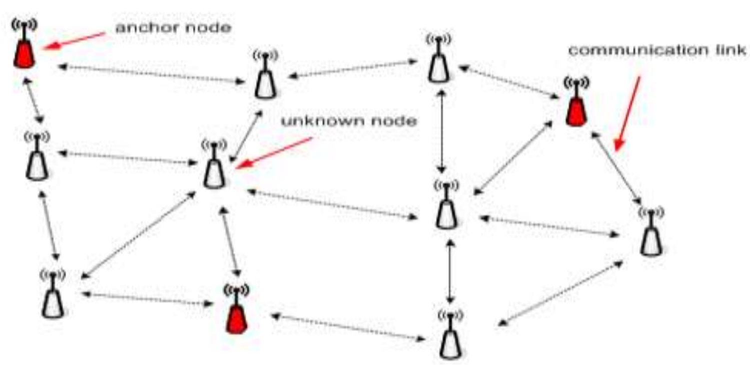

Figure 1 An Example Node Localization.

Fig 1 clearly explains about wireless sensor networks and their relative positions of various nodes. Here, the inter sensor distance mechanism is used to identifies the available nodes in the network. The anchor nodes are a small number of nodes; these are coordinated with GPS or known coordinate positions. These anchor nodes are used to identifies the unknown nodes and calculating the physical position of the remaining nodes. The long-range communication is possible only through more number of nodes. In this, many unknown nodes are presented, and they were consuming high energy for transmission. These nodes can be measured with anchor nodes called a single-hop localization technique. The unknown nodes have been available in the network; these are used to measure the various nodes without any involvement of anchor nodes called as cooperative localization or multi-hop localization. In this case, there may be a chance of 3 or 4 anchor nodes in the network, but they are not connected to unknown nodes. In cooperative localization, two phases are available those are localization phase and measurement phase. In the second phase inter sensor, distance is estimated by using time of arrival(TA), received signal strength(RESS) and time difference of arrival. The measurement phase also possible to calculate through angle arrival(AA), but this mechanism is highly economical. Coming to the localization phase, Many algorithms and optimization models are used to estimating the sensor positions and its uncertainties [3].

Compared to single-hop localization multi-hop localization technology offering many applications such as intrusion detection, target monitoring, road traffic tracking, rescue operations, health monitoring and high-end surveillance [4]. By producing observations between adjacent nodes requires the knowledge to identify the network nature. The frequency or timing of arrival of a signal sent from one node to the other may be specific parameters [2-4]. Conversely, the phase discrepancy between signals concurrently sent at a pair of nodes and obtained at another pair of nodes is used by the Radio Interferometric Positioning Method (RIPS) to compute the number of range discrepancies between both the four nodes [5]. We use RIPS dimensions in our examples since, in reality, they combine precision with a wide range. It is believed here that all the measurements are submitted for analysis to a central node. A complicated issue of parameter calculation is node localization from these measurements. Because the measures are usually non-linear functions of node positions, only computational optimization [6] will find maximal probability figures. To avoid-aggregation to a local-limit, relatively accurate initialization is needed. In a Bayesian system, the node localization issue is discussed in this article. The appropriate estimator in this system, in the mean square error sense, is the posterior level. Since it is not possible to precisely find the posterior distribution, and thus the posterior mean, an estimate is needed. In Bayesian approximation, this is a prevalent issue, and several computational methods of calculation have been suggested [7].In the sense of particle modification, the progressive adjustment method, as initially indicated in [7], is not appropriate for estimating the vast number of parameters usually presents in the issue of node localization. A generalization of the technique is suggested that helps node localization to be substantially more precise. Numerical simulations will be provided, which show that with reasonable computation complexity, the proposed algorithm canlocate large numbers of nodes accurately.

2 Literature survey

In this section node localization methods and their limitations are briefly discussing. Many researchers have investigating on this WSN localization mechanism. In recent years, wireless indoor positioning systems have become quite common. In several uses, such as quality monitoring and inventory control, these technologies have been effectively utilized. This work [15] offers a summary of the current technologies for wireless indoor positioning and aims to identify numerous strategies and systems. Triangulation, situation interpretation, and proximity was analyzed in three standard position prediction schemes. As it is found in most existing schemes or alternatives, we also address position fingerprinting in depth. We then analyze a series of assets from which position systems are measured, and use this method of assessment to sample a variety of established systems. Comprehensive comparisons of output are made, including precision, accuracy, difficulty, scalability, robustness, and expense. A sensor network's essential role is to capture and forward data to its endpoint. Knowing about the position of captured data is also relevant. This sort of knowledge can be accessed from wireless sensor networks (WSNs) utilizing localization techniques. Localization is a means of deciding the location of sensor nodes Localization is the method of identifying the position of nodes and if the sensors have no knowledge of their spatial locations, data and details are worthless. GPS (global positioning system) is the easiest tool for node localization, although if there are a huge set of nodes in a given network, it becomes very costly. To address the problem of localization, several algorithms have been proposed; however, most current algorithms are application-specific and most of the solutions are not appropriate for a broad variety of WSNs.

The 4G and 5G applications are mainly reconfigure on long term evolution (LTE) and Long term evolution advance (LTEA) models. The prime use of wireless sensor networks is the tracking of complex conditions that shift dynamic tracking time. This shift in action is clarified in unpredicted causality of either such external variables or weakness of device designs them. Machine learning methods are known to be effective in reducing the need for excessive upgrade in order to adjust these circumstances. In addition, machine learning-based approaches promote several realistic strategies to optimize resource use and thereby increase the sensor network's lifetime. In this article, detailed literature on machine learning techniques is presented that are used to solve the problem of node localization in wireless sensor networks (WSNs)[8-14]. The strengths and disadvantages of any of the literatures suggested algorithms have been examined and tested against the problem that has been generated.

Table 2 Literature Survey

S No	Proposed technique	Key points	Centralized / distributed	Complexity rating	State of anchor
1	Survey on localization [16]	In this work various localization techniques an its behavior is analyzed	Both	Analysis	Both anchor and No anchor
2	Directionality and triangulation model [17]	WSN nodes directionality is estimating through angular calculation technique	Centralized	Moderate	Anchor
3	Node localization by using Bayesian method [18]	In this work sampling mechanism and progressive correction estimation techniques are used to identifying the position of available nodes in the network	Distributed	Low	Anchor

A comparative table: 2 surveys are provided to help prospective programmers to create conventional technologies that are inadequate for particular localization implementation challenges. Therefore an advanced Machine learning model is required for estimating the Node localization in WSN.In particular, artificial intelligence is used to construct predictive model by gathering algorithms and methods. Machine learning technique is a useful model it has complex themes and trends model make easy and therefore WSNs with considerable ML getting advantages. In this section, some of the theoretical principles and techniques for implementing machine learning in the sense of WSNs are presented. Known algorithms for machine learning are categorized as follows:

The above figure clearly explains about several machine learning models. MLs are dividing into 2 types supervised and unsupervised learning models. The location-aware activity recognition model belongs to the supervisor learning technique. This method can be implemented through the Bayesian mechanism. Node localization is a significant technology that can offer many WSN applications. The position estimation activity computations concentrate on centralized division and getting the results with a moderate level and its working is performed through anchor node support. Bison load localization mechanism quickly identifies the location of nodes in the wireless sensor networks; this mechanism operated with a centralized structure, and intermediate results are obtained. Coming to anchor-node estimation, all nodes are estimated through various WSN optimizations [18].

3 Problem Statement

The WSN localization is a non-linear functional activity, if cannot identify the node position then network estimation and its coordination automatically degraded the performance. The less improvements of mean square error, actual location, estimated target nodes, TA, RESS, AA are degraded WSN activity. The objective function depending on the above parameters and these are less accurate with existed methods. Therefore an advanced machine learning model is necessary to identify the node localization activity.

$$f(x,y) = \frac{1}{M}\sum_{i=1}^{M}\left(\sqrt{(x-x_i)^2+(y-y_i)^2}-\hat{d}_i\right)^2$$

4 Objective

1.A novel implementation of node localization mechanism through s-boosting machine learning technique

2. A real and accurate node localization in WSN through machine learning techniques

3. A node localization and classification in WSN by using machine learning models.

5 Proposed methodology

The figure 2 and 3 clearly explains about node localization mechanism with NN model, in this convolution layer, pooling layer is applied on WSN network and attains the node position and its information [20]. A nonlinear feature between the inputs and outputs can be estimated by training ANN model. In the on-line localization process, when a target is in the monitoring region, the RSS difference values and their matrix indices can be obtained and input into the qualified ANN model, and then the localization dimensions can be determined. The experimental sensor-free localization framework with a WSN interface is checked.

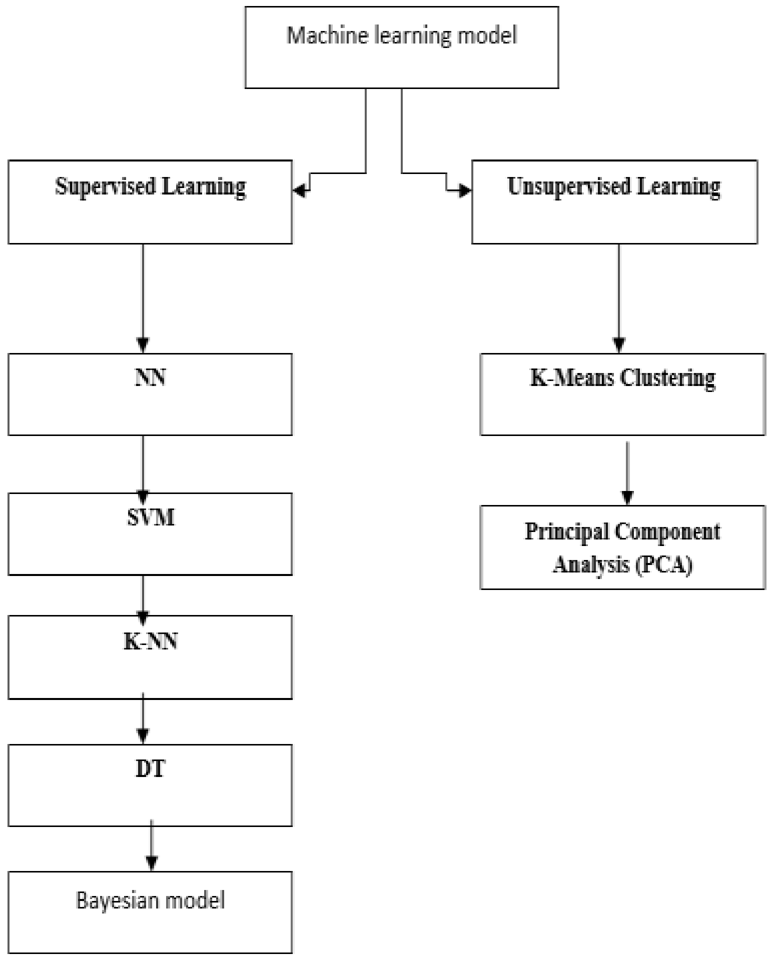

Figure 2 Machine Learning Model for Node Localization

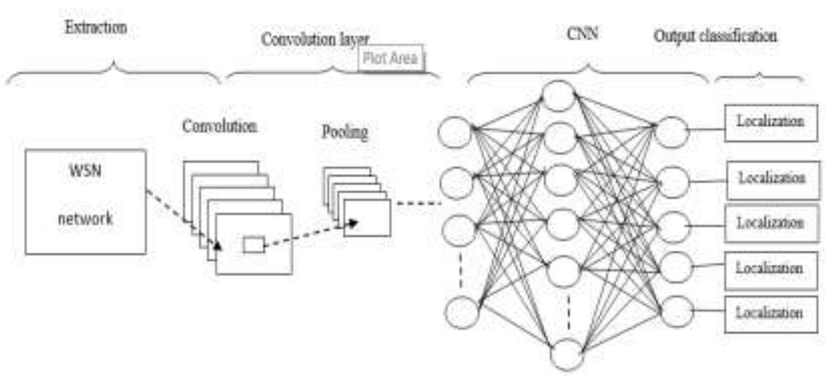

Figure 3 NN based Node localization in WSN

A Two Wireless Sensor Networks (WSN) model is a sophisticated localization scheme. The two systems presented in this paper demonstrate range-free localization, utilizing the path length generated (PLS) from the cluster heads. For both frameworks, soft computing plays a key function. We recognize the edge weight of each anchor node independently during the first structure and combine them to determine the position of sensor network [29].

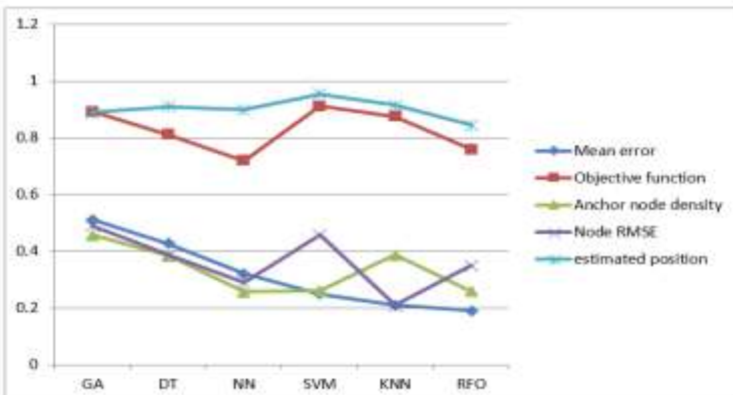

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Figure 4 Estimation of Results

Following a standardized propagation, nodes are uniformly deployed around the surroundings; this allows one to assume that the distribution of the nodes is constant and each node has a specified average number of nodes. Each duration, any node gives a signal; all simulations are 300 units long;. Inside the deployment area, costly anchors should not be used. Instead, it is only possible to position anchors on the edges of the deployment area, which are presumed to be stable, shown in fig 4

γ_{im} = -$[\frac{\partial L(y_i, F(x_i))}{\partial F}]_{F(x)=F_{m-1}(x)}$ for i=1… n ------------ (1)

We gave the values sent by Anchors a substantial weight, multiplying the learning function of equation 4 by a factor w=3. The weight used in the role of the mass core of formulas 6 and 7 is m = 1 for the actual nodes and m = 0.2 for the nodes missing; Designers only examined square deployment areas (lOx1O, 15x15 and 20x20 nodes) to improve the study of the simulated results [30-31].

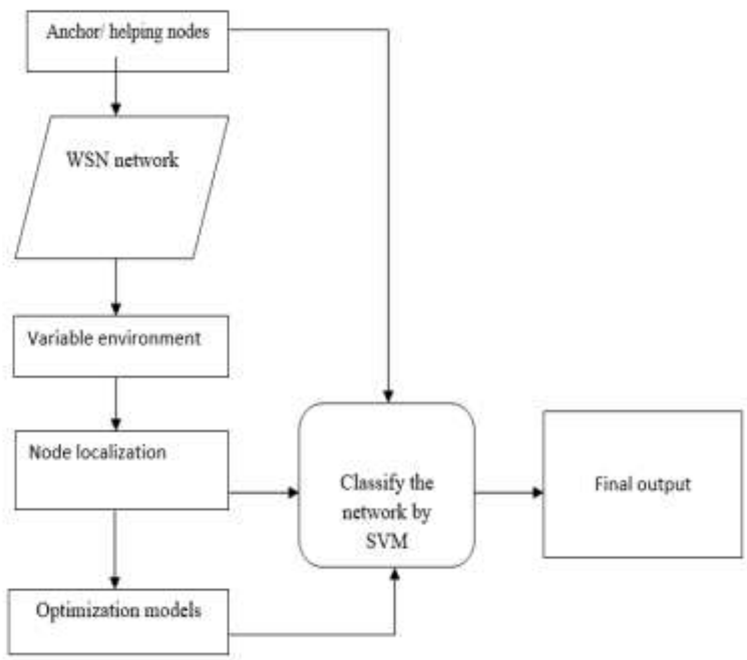

Figure 5 SVM Model

Figure 5 clearly explains about SVM machine learning model for classifying the node localization methods. In this at the input stage, local nodes are assigned for investigating the available WSN environment. WSN is a variable dynamic network so that its analysis is very complex. Due to this variable nature, it cannot estimate the functionality of WSN. Therefore an advanced node localization technology is necessary [33-34]. The above section SVM machine learning classification and its operation are estimated. In this many limitations are faced by basic machine learning model [35]. Moreover, new technology is helping out for communication and proper results.

6 Experimental Result

The machine learning models like path determination distributed localization spatial Gaussian process; self organize mapping, neural networks and reinforcement [20-25] is implemented but facing many issues. So that advanced technology is required in machine learning models.

$$\text{MCC} = \frac{TP.TN-FP.FN}{\sqrt{(TP+FP).(TP+FN).(TN+FP).(TN+FN)}} \quad \text{-------------} \ (2)$$

(MCC: worst value = -1; best value = +1)

$$F_1\ score = \frac{2.TP}{2.TP+FN+FP} \qquad \text{------------------- (3)}$$

$$(F_1\ score : worst\ value = 0; best\ value = 1)$$

$$sensitivity = \frac{TP}{TP+FN} \qquad \text{-------------------------------- (4)}$$

$$(sensitivity: worst\ value = 0; best\ value = 1)$$

$$specificity = \frac{TN}{TN+FP} \qquad \text{---------------------------- (5)}$$

$$(specificity: worst\ value = 0; best\ value = 1)$$

Above all equations are mainly used for calculating the performance estimation parameters; these are useful for comparing the designed application with existed methods.

The above equation from 2 to 5 demonstrates that various performance measures of machine learning models with respect to the WSN node localization mechanism.

Table 3 Comparisons of Results

	Mean error	**Objective function Estimation**	**Anchor node density**	**Node RMSE**	**estimated position**
GA	0.512	0.8925	0.458	0.489	0.89
DT	0.428	0.812	0.384	0.387	0.91
NN	0.321	0.719	0.258	0.289	0.899
SVM	0.25	0.912	0.26	0.458	0.954
KNN	0.21	0.8759	0.387	0.21	0.915
RFO	0.19	0.759	0.259	0.35	0.8457

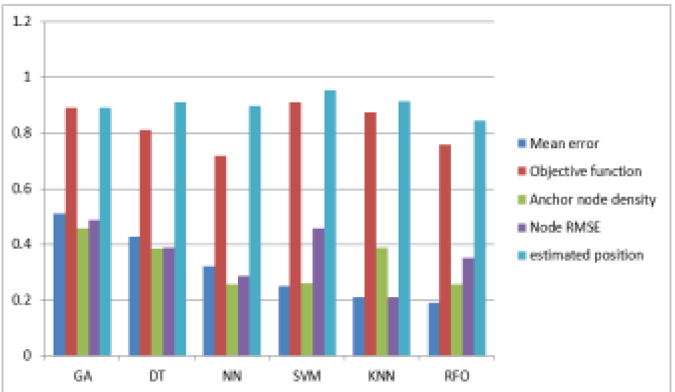

Figure 6 various node localization methods

Figure 6 and table 3 clearly explains about various node localization methods with respect to conventional and machine learning techniques. In this the methods like genetic algorithm, decision trees, neural networks, SVM, KNN and random forest optimization models and its operations are explained. It is clearly identified that proposed models are facing many limitations and WSN communication issues

7 Conclusion

In this paper different node localization techniques are discussed through conventional machine learning models. The earlier methods do not handle the WSN dynamic nature. So that node localization and its estimation tense to miss detection. Without localization WSN cannot handle the applications with accurate manner. The performance errors like mean square error, node RMSE, objective function and estimated position values are getting less improvement. Therefore an advanced machine learning model is necessary for node localization purpose.

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