Journal of Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.7760160

MACHINE LEARNING BASED SINK NODE POSITION ESTIMATION IN WIRELESS SENSOR NETWORK HAVING MOBILE NODES

R.Padmaraj[1], K.Selvakumar[2],
Department of Information Technology, Annamalai University,
thillaikoothan@gmail.com[1], kskaucse@gmail.com[2]

ABSTRACT

All of the information gathered by the sensor nodes in wireless sensor networks (WSNs) is sent to a sink node. As a result, the location of the sink node greatly affects the amount of energy used and the lifespan of WSNs. This study examines the placement methods for sink nodes that are lifetime- and energy-oriented in single-hop and multiple-hop WSNs, respectively. The lifetime-oriented method places a far greater emphasis on the lifespan of the nodes that consume energy at the fastest rate than the energy-oriented strategy, which solely takes into account lowering network energy consumption overall. The aim is to investigate the effectiveness of an artificial intelligence based solution to the problem of identifying the optimal position of the sink node. The objective is to reduce the overall energy spent in data transmission and increase the network life time. The optimal location of a sink node will be determined using a gradient boosted regression model. The location of the sink node is estimated with reference to the nodes present in the network. It is assumed that the lifetime of the network completes immediately when the first node fails.

Keywords: *wireless sensor networks, sink node, energy consumption, gradient boosted regression, network lifetime,*

INTRODUCTION

Due to their wide application and future potential [1 - 5], wireless sensor networks (WSNs) have drawn a lot of attention from academics. The sensor nodes and the sink node are a WSN's two primary building blocks. The signals produced by the sensor nodes are given to the end users through the sink nodes, regardless of the fact that wireless sensor networks (WSNs) are potential of having a range of topologies, such as star, mesh, or ring. A sink node, often known as a base station, is essentially a stronger version of a sensor node. Building a bridge between a WSN and the distant users is one of the sink node's main responsibilities (Fig. 1). WSNs actually differ from ad hoc networks in that their sensor nodes are driven by non-rechargeable batteries. The development of new protocols [9–10] and approaches [6–8] to extend the life of the network are therefore crucial. For every single sensor node, the amount of energy needed to transmit a signal to the base station is dependent upon the distance and quantity of hops that message must make. It would be easier to deliver messages with less energy and extend the life of the network if there were multiple sink nodes that were used effectively inside the network field. However, there are certain limitations to using multiple sink nodes, such as the expense of the equipment or the infeasibility of having more than one within the field. The location of the sink node can have an impact on the overall network performance since the sensed data acquired by conventional SNs is sent to the base station. Finding the ideal location for the sink node inside the network field presents a number of difficulties.

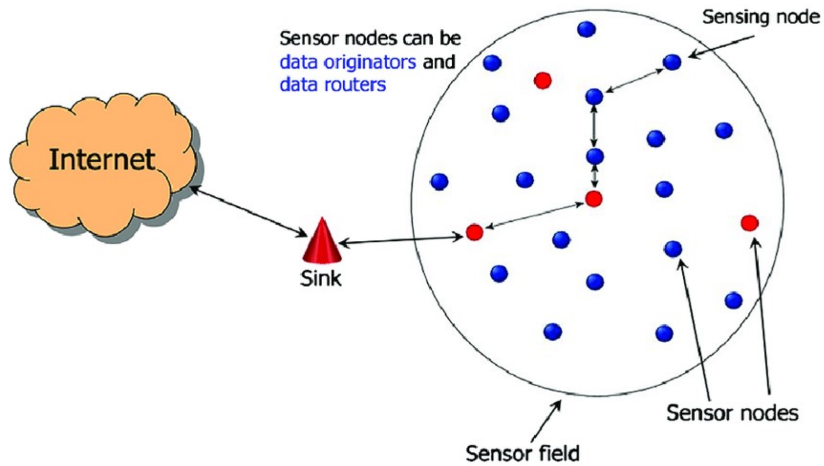

Fig. 1 Architecture of WSN [12]

Here are a few of the major problems:

- The sink node can potentially be situated anywhere inside the network field because there is a large solution space.
- Another significant obstacle to finding the sink node in WSNs is the enormous number of sensor nodes.
- There are numerous routing protocols, each with a unique energy model and method for routing data to the base station.
- Potential network topology changes brought on by failures or enhancements that would necessitate moving the sink node.
- Different considerations may be necessary when optimizing the sink node position for periodic or event-driven sampling modes.
- The sink node must be moved in order to increase the network's throughput and lifespan as sensor nodes are added to the network field.

In order to reduce the total distance from all nodes to the base station, this study aims to determine the optimal position for the base station. Several studies use the geometric median of all the locations connected to the sensor nodes to choose the best placement. The geometric median in a discrete set of points can be thought of as the place that, in essence, minimizes the sum of perpendicular distance between base station and all the sensor nodes. The existing methods for estimation of geometric mean is computationally expensive. The base station location plays a crucial part in assuring the dependability and independence of the wireless sensor network. As a result, great effort should be taken when positioning the sensor nodes in the area of interest so that the overall energy spent in the network is minimized.

The energy hole problem is brought on by the battery restriction, which causes the base station nodes to be the first nodes to run out of energy as a result of being burdened by the reliance job from the remote nodes. As a result, the energy hole problem is covered in a lot of literature. The energy hole problem has been addressed in a number of ways, including sink mobility, assigning sensor nodes multiple transmission powers, and distributing the initial energy budget unevenly.

The sensed data that are gathered by the standard sensor nodes in wireless sensor networks (WSNs) must be transmitted to the base station in order to be accessed by the remote users.

The position of the sink may have a big impact on the network's throughput and energy consumption. In order to minimize the total hop-distance from all the sensor nodes to the sink node, this study investigates the best deployment location for the base station. The rest of the paper is organized as follows. The relevant work and proposed solution for base station location estimation are presented in Section 2. The method and algorithm we used to locate the sink node's ideal location are discussed in Section 3. Section 4 presents the network model together with numerous simulation-related parameters. The performance evaluation is found in Section 5, the outcome of our simulation, and the work's conclusion are found in Section 6, respectively.

LITERATURE SURVEY

Various literature put forth WSN maximization methods that gathered data from WSN sensor nodes using a single mobile sink. Based on where the decision-making occurs, these models are divided into centralized and dispersed categories. They differ according to their movement, which might be discrete or semi-continuous. There were numerous centralized sink mobility models suggested. To estimate the sink movement and pause length in a grid network topology, for example, [13] suggested a combined approach. According to the recommended algorithm, there is only one unique path between a sensor node and a sink when they are situated along the same vertical or horizontal axis, and that path is the direct one. Otherwise, just the two routes with an identical number of hops as disclosed by the rectangle whose edge a sensor I and a sink define are taken into consideration. A data gathering approach that makes advantage of several mobile nodes acting as sink nodes was proposed in [14]. The primary objective is to improve the path planning process. A dynamic clustering method that randomly groups the nodes into groups is the basis of the algorithm. The cluster head for the data collecting cluster is chosen as the node with the maximum energy. For the majority of formulations of sensor deployment, optimal node placement has been shown to be an extremely difficult problem that is NP-Hard [15-17]. Several strategies have been presented to identify less-than-optimal solutions to this complexity [18–20]. However, the environment of these optimization algorithms is primarily static in that it bases its analysis on a predefined topology and uses structural quality metrics like distance and network connectedness to evaluate the quality of candidate places. They can be categorized as static techniques as a result [24-27].

The optimality of the starting placements may be nullified throughout network operation based on the network state and different external factors, hence some strategies have, on the other hand, advocated dynamic adjustment of node location [21–23]. For instance, traffic patterns may alter in response to events being tracked, or the load may not be distributed evenly among the nodes, leading to bottlenecks. Also, when new nodes join the network or as existing nodes run out of energy, application-level interest can change over time and the resources that are now available on the network may also change. Nonetheless, in some situations, random node distribution is the only practical choice. This is especially true in difficult environments like a war zone or a catastrophe area. Random node deployment can meet the necessary performance objectives, depending on the node dispersion and level of redundancy. Nonetheless, in some situations, random node distribution is the only practical choice. This is especially true in difficult environments like a war zone or a catastrophe area. Random node deployment can meet the necessary performance objectives, depending on the node dispersion and level of redundancy [28-31].

Application developers prefer that the sensors are used in a way that is consistent with the general objectives of the design. Thus, the majority of the suggested node placement strategies in the literature have concentrated on raising data fidelity, extending network lifetime, and/or ensuring robust network connectivity. Secondary goals like load balancing and node failure tolerance have also been taken into account.

EXISTING SINK NODE PLACEMENT STRATEGIES

Under energy-oriented model the energy consumed for transmitting and receiving data packets were considered. Let $E_{TX}(d)$ and E_{RX} represents the energy consumption for transmission and reception of a 1-bit sized data.

$$E_{TX}(d) = E_{elec} + \varepsilon_{amp} d^2 \qquad \text{Eq. 1}$$

$$E_{RX} + E_{elec} \qquad \text{Eq. 2}$$

d- distance between the transmitter and receiver

E_{elec} – energy consumed by the transceiver

ε_{amp} – Amplification co-efficient

There are two ways to calculate the networks' overall energy consumption per unit of time. The first approach involves summing the energy usage of each node. Each node's estimated data sending and receiving capacity per unit of time. The energy consumed by each node is then calculated using (1) and (2), and an estimate of the overall energy consumption of all nodes per unit of time is then possible. In the second way, the energy spent in each route is added. First, an estimation of each node's rate of data creation is made. The energy consumed over a unit of time for each source node's travel to the sink is then calculated. The sum of the energy consumed along each route represents the overall energy consumption per unit of time.

Let R denote the maximum transmission range of a sensor node and S_i denotes the communication region of the sink which can be expressed mathematically as;

$$S_i = \left\{(u, v) \mid (u, v) \in S, \sqrt{(u - x)^2 + (v - y)^2} \le R_c \right. \qquad \text{Eq. 3}$$

The sink node placement that results in the least amount of energy consumption is found via the energy-oriented solution. When considering the lifetime in WSNs, it is typically not the best option. For instance, if the location of the solution is in an area with a very low sensor density, there won't be enough sensor nodes nearby the sink to relay the data, resulting in a reduced network lifetime. Even though the energy usage in the networks is not very low, we prefer to install the sensors in areas with a higher sensor density.

Energy-Based strategy

The energy oriented sink node placement strategy was studied in [11, 25], and this section briefs the same technique under a stochastic distribution environment. The energy consumption of node (when transmitting 1-bit of data via a h-hops route) can be computed as follows;

$$\delta_m = \begin{cases} E_{TX}(d_m) = E_{elec} + \varepsilon_{amp} d_m^2, m = 0 \\ E_{RX} + E_{TX}(d_m) = 2E_{elec} + \varepsilon_{amp} d_m^2, m = 1, 2, \ldots, h - 1 \end{cases} \qquad \text{Eq. 4}$$

d_m – transmission distance of the m^{th} hop
δ_m – energy consumed for transmitting 01-bit data via h hops. The energy consumed in the sink node is neglected and the energy consumed in the h-1 intermediate nodes are considered. With reference to the above mathematical expression the total energy consumption Θ_i in the network when a transmitted sends a one bit size packet to the sink node;

$$\Theta_i = (2H_i - 1)E_{elec} + \varepsilon_{amp} \sum_{m=0}^{H_i-1} D_{im}^2 \qquad \text{Eq. 5}$$

D_{im} and H_i are variables of transmission distance and hop length. Accurate estimate of the above value i.e overall energy consumed in the network cannot be made and hence the following approximation methods are used.

i. The hop length of the transmission route is proportion to the distance between the transmitter and the receiver node, i.e $H_i = cD_i$; D_i – distance between the transmitter and the destination node and c is a constant whose value is greater than zero.
ii. The value of D_{im}^2 is independent of H_i; so that $ED_{im}^2 = \sigma; where\ \sigma > 0\ is\ a\ constant.$

As per the network model, each node follows the same probability density function $f(u, v)$. In the energy-based strategy the $g(x, y)$ can be expressed mathematically as follows [25];

$$g(x,y) = E\left[\sum_{i=1}^{N} \Theta_i\right] = E\left\{\sum_{i=1}^{N}\left[(2H_i - 1)E_{elec} + \varepsilon_{amp} \sum_{m=0}^{H_i-1} D_{im}^2\right]\right\} \qquad \text{Eq. 6}$$

$$= \sum_{i=1}^{N}(2E_{elec}E\,H_i + \varepsilon_{amp}ED_{im}^2H_i - E_{elec})$$

$$= \left(2E_{elec} + \varepsilon_{amp}\sigma\right)N_cED_i - \mathrm{N}E_{elec}$$

It was observed that $N_c\left(2E_{elec} + \varepsilon_{amp}\sigma\right) > 0$, hence $g(x, y)$ can be minimized as given in [25]

$$g(x,y) = ED_i = \iint_{(u,v)\in S} \sqrt{(x-u)^2 + (y-v)^2} f(u,v)dudv \qquad \text{Eq. 7}$$

PROPOSED METHODOLOGY

The focus of the work is to maximize the design objectives using the network resources, such as nodes. Achieving the design goals with random node distribution is quite difficult. Although seemingly the proposed sink node placement strategy can potentially satisfy all major and secondary objectives, the struggle to use up as few network resources as possible makes the challenge even more challenging. Even in deterministic deployment settings, optimal sensor placement is a challenging issue. A sensor's capacity to detect an object may be unclear owing to distortion that may be brought on by geography or the sensor's presence in a hostile environment, and complexity is frequently introduced by the effort to use the fewest number of sensors possible in order to meet application requirements. The main goal of the suggested strategy, which greatly influences network lifetime through node locations, is to extend network lifetime. For instance, differences in node density can eventually result in an uneven traffic load and bottlenecks throughout the area. According to the simulation research, a uniform node distribution may cause nodes adjacent to the base station to lose energy more quickly than other nodes, reducing the network lifetime.

This study examines sensor placement strategy with coverage restrictions to maximize lifespan. It is assumed that every sensor delivers its data report to the base station or a sink node on a regular basis. Over the longest period of time, the network must encompass a number of interesting locations. The metric for calculating the sensor lifetime is the average energy usage in each data collection round. By distributing the load among the sensors, the issue is then changed to focus on minimizing the average amount of energy used by a sensor in every iteration of the transmission. The sensor is tested to see if it can relocate to a different area and act as a relay in each iteration. The new position is determined by the volume of traffic and the data path that this node is currently or will soon join. Fundamentally, by moving closer to its downstream neighbor, the migrating node should use less energy. Only when there is no chance of a coverage loss then a sensor is permitted to reposition.

It is assumed that a number of fixed sensors are often placed in well-known locations, and the objective is to determine target placements as precisely as possible. The approach is to develop a system model for the issue in order to place the sink node with respect to the reference nodes. Let us assume a two dimensional wireless network with N reference nodes and M sink nodes. The unknown positions of the M target nodes are represented as $x_i = [\, x_{i1}\, x_{i2}]^T \in \mathbb{R}^2, i = 1, \dots \dots, M$ and the known position of the N nodes are represented as $a_j = [a_{j1} a_{j2}]^T \in \mathbb{R}^2, j = M+1, \dots \dots, N+M$. The target sink node can communicate directly with a subset of reference nodes and few other sink nodes.

$$A_i = \{j \mid sink\ node\ i\ can\ communicate\ with\ reference\ node\ j\} \qquad \text{Eq. 8}$$

$$B_i = \{j | i \neq j, sink\ node\ j\ can\ communicate\ with\ sink\ node\ i$$

A_i and B_i represents the set of indices of references and sink nodes that lies in the transmission range of node i.

$$m_{ij} = \begin{cases} f(x_i, a_j) + \epsilon_{ij}, & j \in A_i \\ f(x_i, x_j) + \epsilon_{ij}, & j \in B_i \end{cases} \qquad \text{Eq. 9}$$

The m_{ij} represents a measured value between the nodes with reference to their positions. The deterministic function $f(\alpha, \beta)$ represents a measured value among two different sensor positioned at α and β and ϵ_{ij} represents the noise. The objective is to minimize the following cost function using regression algorithm;

$$\hat{X} = \arg\min_{X\in\mathbb{R}^{2\times M}} \sum_{i=1}^{M}\left(\sum_{j\in A_i}(m_{ij} - f(x_i, a_j))^2 + \sum_{j\in B_i}(m_{ij} - f(x_i, a_j))^2\right) \quad \text{Eq. 10}$$

NETWORK SIMULATION

The conventional model that was once used to analytically analyze system behavior is no longer useful due to the increase in complexity of communication networks. In order to accurately comprehend the behavior of the system, a model must be created. Before building its hardware implementation, the newly proposed model or method is implemented through simulation. To ensure a system's performance and functionality, simulation is used. The simulation study's implementation of the OFDM-based IEEE 802.11 standard, PhySim-WiFi, is thorough and accurate. The PhySim-WiFi integration simulates the underlying signal processing steps of a transceiver down to the signal level, increasing accuracy for the determination of whether a packet could be correctly received or not. This is in contrast to the default 802.11 PHY standard, which abstracts packets by assessing only an average transmission power per packet and the length of the packet. More complex channel models can now be incorporated thanks to the improved implementation. For instance, channel models can more precisely simulate multi-path effects and can represent Doppler phenomena and their effect on the physical layer signal processing method since packets are modelled at the signal level. By deciding that devices in the same area will share the allotted frequencies, the MAC layer establishes connections to the PHY channel. In this layer, data packet scheduling and routing are also managed. Many tasks, including consistent communication between two peer-to-peer MAC devices, are carried out by the 802.15.4 MAC layer.

The simulation used the Advanced Encryption Standard (AES), which is based on the IEEE 802.15.4 standard and uses a 128-bit key length as the fundamental encryption technique, for data security. The frame format and several of the payloads are drastically changed when such security mechanisms are activated for 802.15.4. The Security Enabled field in the Frame Control section of the 802.15.4 header must be used as the first step in the AES encryption activation process. This field has a single bit that is set to 1 for safety. When this bit is set, a field called the Auxiliary Security Header is created after the Source Address field by stealing a few bytes from its Payload field.

Table1. Simulation Parameters

Parameter	Value
Simulation Time	30 -60 mins
No. of mobile nodes	50 - 200
No. of sink nodes	02 - 08
Max. speed of mobile node	20 m/s
Network area	1500m x 3000m

MAC	IEEE 802.15.4
Node Mobility	Random waypoint
Queue length	50
Traffic	Constant bit rate
Physical Layer	IEEE 802.11 PhySim-WiFi

The simulation generates the data required for modeling the location estimation algorithm. During the simulation process the position of the sensor nodes and the respective remaining energy level are recorded. The total energy spent by $h-1$ intermediate node in transmission of the data packets were recorded. The position of the sink nodes were also recorded with respect to the location of the sensor nodes. These data are used for building regression model which could estimate the optimal position of the sink nodes with reference to the location of the mobile sensor nodes. For assessing the performance of the proposed regression based position estimation approach it is compared with the energy-based position estimation strategy described in the Section 3.

The cost function mentioned in the Eq. 10 is minimized using support vector regression (SVR) with gaussian kernel, a non-linear regression analysis. Finding a function that approximates the mapping from the input domain to the actual number in the training sample is difficult when using regression. SVR focuses mostly on taking into account factors within a decision's parameters. The popular SVR algorithm allows for flexibility and error tolerance through the use of both a reasonable error margin (ϵ) and an acceptance adjustment that is greater than the acceptable error rate.

RESULTS AND ANALYSIS

The experiment employed a various numbers of sensor nodes, ranging between 100, and 600 nodes. The sensor nodes are dispersed at random in a 2-D area of 1500 x 3000 m2. The deployment location of the sink node is chosen using the proposed approach. Each sensor node has a communication module that is identical, allowing for equivalent communication and sensing distances. The communication radius in the experiment is set to 40 m. Moreover, the energy used for sending and receiving the data is included in the total energy use. One data package's energy consumption for reception is intended to be 40% lower than for transmission. A sensor node's energy level is arbitrarily set between a range of 1000 and 2000. A sink node positioning methodology based on optimization of the Eq. 7 using the Particle Swarm Optimization (PSO) method is contrasted with our suggested strategy. This programme tries to create a topology control protocol that is energy aware.

Table 2. Comparing the energy consumption

# of nodes	Energy based strategy	Proposed regression based method

100	14.0338	10.2145
200	20.8981	18.8562
300	27.8352	26.1232
400	40.3712	35.4526
500	46.7464	45.2865
600	61.8228	52.6541

The network node count, with overall power usage when energy-based and proposed sink node location estimators were used are shown in Table 2. For instance, in a 100-node system, the total power usage with PSO and the suggested techniques is 14.0338 and 10.2145, respectively. In all test situations, it is obvious that the proposed approach's overall power consumption is lower than the energy-based strategy approach's. Before using the greedy method to create the transmission route, the suggested technique or energy based approach determines the sink node position.

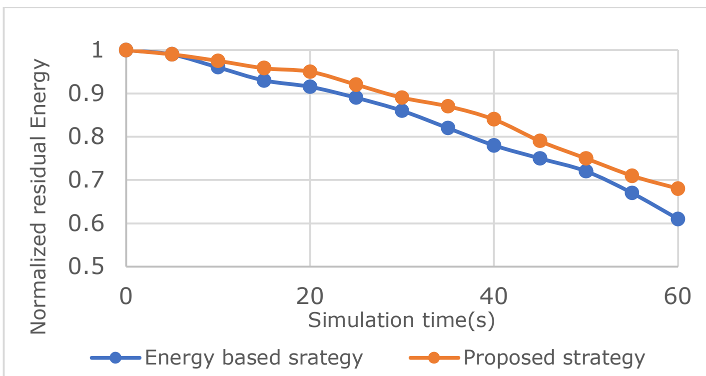

Fig. 2 Residual Energy Comparison

The performance of the proposed sink node placement strategy is compared with the energy based strategy in terms of residual energy available in the network during the simulation time. The energy based strategy sink node placement strategy consumes more energy when compared to the proposed regression analysis based sink node placement method. Similarly when comparing the lifetime of the network, the energy based strategy has lesser lifetime. As the sink nodes are placed in optimal position using the regression based technique the overall lifetime of the network is increased. The regression analysis based sink node location estimation reduces the sum of perpendicular distance between the sink or base station and the sensor nodes. When mobile nodes are deployed in the network region for sensing the network information, this sink node location estimation is done repeatedly depending on the transmission coverage. A centralized network coverage monitoring is scheduled periodically which assess whether all the sensor nodes are in the transmission range of the base station. If one or few of the nodes drift away from the base station coverage then the sink node positioning strategy is executed with respect to the position of the individual sensor nodes using the regression model. This helps to limit the overall energy consumed in the network by avoiding the packet loss and subsequent re-transmission of the lost packets.

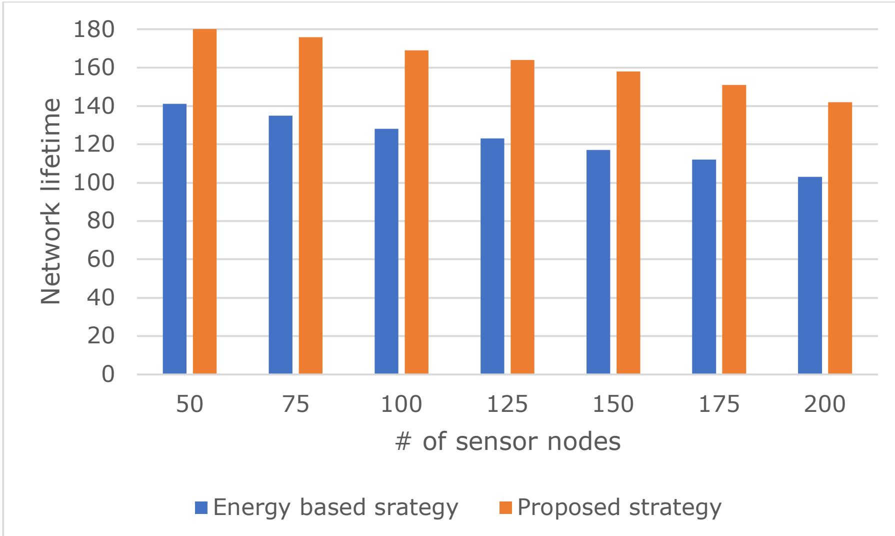

Fig. 3 Network lifetime Comparison

CONCLUSION

Ad-hoc network formation and the resource-constrained nature of sensor nodes, which are frequently combined with unattended deployment, present non-traditional issues and drive the need for specialized methodologies for developing and operating WSNs. The impact of node placement techniques on the functionality and effectiveness of WSNs has been analyzed in this work. An approach based on machine learning is suggested in this research to determine where the sink nodes should be placed. The suggested network uses less energy and has a longer lifespan than the conventional energy-oriented strategy. Our study is conducted in mobile-sink WSNs. The mobile sensor node network's machine learning (regression) model was expanded from the single-sink example to include multiple sink nodes. However, the complexity of the model is a little bit higher and has to be decreased after more research. The findings of the simulation study showed that dynamic node positioning after deployment or during regular network operation can be a practical strategy for improving the network's overall performance.

REFERENCE

1. G. Werner-Allen, K. Lorincz, M. Ruiz, O. Marcillo, J. Johnson, J. Lees, et al. Deploying a wireless sensor network on an active volcano IEEE Internet Comput, 10 (2) (2006), pp. 18-25
2. M.P. Durisic, Z. Tafa, G. Dimic, V. Milutinovic A survey of military applications of wireless sensor networks," Mediterranean conference on embedded computing (MECO) (2012), pp. 196-199
3. Ko JeongGil, Lu Chenyang, M.B. Srivastava, J.A. Stankovic, A. Terzis, M. Welsh Wireless sensor networks for healthcare Proc IEEE, 98 (11) (2010), pp. 1947-1960
4. J. Gubbi, R. Buyya, S. Marusic, M. Palaniswami Internet of Things (IoT): a vision, architectural elements, and future directions Futur Gener Comput Syst, 29 (7) (2013), pp. 1645-1660

5. Jun Huang, Yu Meng, Xuehong Gong, Yanbing Liu, Qiang Duan A novel deployment scheme for green Internet of things IEEE Internet Things J, 1 (2) (2014), pp. 196-205
6. Jiang Fuu-Cheng, Yang Chao-Tung, Teng Shih-Meng, Wu Hsiang-Wei, Chiang Yi-Ju Modeling and prolonging techniques on operational lifetime of wireless sensor networks 2010 IEEE 13th international conference on computational science and engineering (CSE) (2010), pp. 6-13
7. Md Nafees Rahman, M.A. Matin Efficient algorithm for prolonging network lifetime of wireless sensor networks Tsinghua Sci Technol, 16 (6) (2011), pp. 561-568
8. Jaekyu Cho, Jeongkeun Lee, Taekyoung Kwon, Yanghee Choi Directional antenna at sink (DAaS) to prolong network lifetime in wireless sensor networks 12th European wireless conference 2006 - enabling technologies for wireless multimedia communications (European Wireless) (2006), pp. 1-5
9. Y. Tamandani, M. Bokhari SEPFL routing protocol based on fuzzy logic control to extend the lifetime and throughput of the wireless sensor network Wireless Netw (2015)
10. Yanjun Yao, Qing Cao, A.V. Vasilakos EDAL: an energy-efficient, delay-aware, and lifetime-balancing data collection protocol for wireless sensor networks 2013 IEEE 10th international conference on mobile ad-hoc and sensor systems (MASS) (2013), pp. 182-190
11. Vincze, Z., Vida, R., & Vidacs, A. (2007). Deploying multiple sinks in multi-hop wireless sensor networks. In 2007 IEEE international conference on pervasive services, Istanbul, Turkey, 15–20 July 2007.
12. Mihoubi, Miloud & Rahmoun, Abdellatif & Lorenz, Pascal & Lasla, Noureddine. (2017). An effective Bat algorithm for node localization in distributed wireless sensor network. Security and Privacy. 1. 10.1002/spy2.7.
13. Z. M. Wang, S. Basagni, E. Melachrinoudis, and C. Petrioli, "Exploiting Sink Mobility for Maximizing Sensor Networks Lifetime," in Proceedings of the 38th Annual Hawaii International Conference on System Sciences, Jan. 2005, pp. 287a–287a, iSSN: 1530-1605
14. Pang, A.; Chao, F.; Zhou, H.; Zhang, J. The Method of Data Collection Based on Multiple Mobile Nodes for Wireless Sensor Network. IEEE Access 2020, 8, 14704–14713.
15. A. Efrat, S. Har-Peled, J.S.B. Mitchell, Approximation algorithms for two optimal location problems in sensor networks, in: Proceedings of the 3rd International Conference on Broadband Communications, Networks and Systems (Broadnets'05), Boston, Massachusetts , October 2005.
16. X. Cheng, DZ Du, L. Wang, B. Xu, Relay sensor placement in wireless sensor networks, ACM/Springer Journal of Wireless Networks, in press.
17. S. Poduri, S. Pattem, B. Krishnamachari, G.S. Sukhatme, Sensor network configuration and the curse of dimensionality, in: Proceedings of the 3rd IEEE Workshop on Embedded Networked Sensors, Cambridge, MA, May 2006.
18. J. Pan, L. Cai, Y.T. Hou, Y. Shi, S.X. Shen, Optimal basestation locations in two-tiered wireless sensor networks, IEEE Transactions on Mobile Computing 4 (5) (2005) 458–473.

19. S.S. Dhillon, K. Chakrabarty, Sensor placement for effective coverage and surveillance in distributed sensor networks, in: Proceedings of the IEEE Wireless Communications and Networking Conference (WCNC'03), New Orleans, LA, March 2003.
20. T. Clouqueur, V. Phipatanasuphorn, P. Ramanathan and K.K. Saluja, Sensor deployment strategy for target detection, in: Proceedings of the 1st ACM international Workshop on Wireless Sensor Networks and Applications (WSNA '02), Atlanta, Georgia, September 2002.
21. Prasad, T. G., Turukmane, A. V., Kumar, M. S., Madhavi, N. B., Sushama, C., & Neelima, P. (2022). Cnn Based Pathway Control To Prevent Covid Spread Using Face Mask And Body Temperature Detection. Journal of Pharmaceutical Negative Results, 1374-1381.
22. M. Sunil Kumar, "Forecasting of Wind Power using LSTM Recurrent Neural Network." Journal of Green Engineering 10 (2020).
23. K. Akkaya, M. Younis, M. Bangad, Sink repositioning for enhanced performance in wireless sensor networks, Computer Networks 49 (2005) 434–512.
24. G. Wang, G. Cao, T. La Porta, W. Zhang, Sensor relocation in mobile sensor networks, in: Proceedings of the 24th International Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM05) Miami, FL, March 2005.
25. J. Wu, S. Yang, SMART: A scan-based movement assisted sensor deployment method in wireless sensor networks, in: Proceedings of the 24th International Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM'05), Miami, FL, March 2005.
26. Davanam, G., Kumar, T. P., & Kumar, M. S. (2021). Efficient energy management for reducing cross layer attacks in cognitive radio networks. Journal of Green Engineering, 11, 1412-1426.
27. Balaji, K., P. Sai Kiran, and M. Sunil Kumar. "Power aware virtual machine placement in IaaS cloud using discrete firefly algorithm." Applied Nanoscience (2022): 1-9.
28. Kumar, M. Sunil, et al. "Deep Convolution Neural Network Based solution for Detecting Plant Diseases." Journal of Pharmaceutical Negative Results (2022): 464-471.
29. Davanam, G., Pavan Kumar, T., & Sunil Kumar, M. (2021). Novel Defense Framework for Cross-layer Attacks in Cognitive Radio Networks. In International Conference on Intelligent and Smart Computing in Data Analytics (pp. 23-33). Springer, Singapore.
30. M. M Fouad, V. Snasel, and A. E Hassanien, Energy-Aware Sink Node Localization Algorithm for Wireless Sensor Networks, International Journal of Distributed Sensor Networks, 2015.
31. Chen, Fengchao, and Ronglin Li. "Sink node placement strategies for wireless sensor networks." *Wireless personal communications* 68 (2013): 303-319.