# A Performance Survey and Simulated Residual Energy of Sensor Nodes in a Typical Wireless Sensor Network

O. J. Odeyinka[1], O. A. Ajibola[2*], O. K. Akinde[1], A. O. Akande[3] and A. O. Ilori[1]
[1]Department of Electrical and Biomedical Engineering, Faculty of Engineering, First Technical University, Ibadan, Nigeria
[2]Department of Electrical and Electronics Engineering, Faculty of Engineering, University of Lagos, 100213 Akoka, Lagos, Nigeria
[3]Department of Electrical and Electronics Engineering, Faculty of Engineering, Federal University of Technology, Owerri, Nigeria
[*]corresponding author's email: ajibolaoa@yahoo.com

**Abstract** - *This paper is a performance survey on the residual energy of nodes in a wireless sensor network (WSN). Wireless sensor nodes are limited in application due to constraints in energy of nodes' battery and addressing the problem of energy management is essential to lengthen the life of a deployed network of wireless sensors. In the method used, Sensor nodes were equally distributed on the complete border of the network field. An exclusive cluster, six hierarchical, and eighteen hierarchical clusters were formed based on even partition of the border of the network field. The choice of Cluster Head (CH) within each cluster formed was based on selection of a sensor node with minimal transmission distance to the Base Station. A comparison of the various hierarchical scenarios was simulated in MATLAB. The mean residue energies (MREs) after the network lifetime are 3%, 52%, and 35% of the initial node energy for single, six and eighteen hierarchical clusters respectively. The residual energies of sensor nodes above the recorded MREs were taken on a class interval of 50's of the node identity (nid) and respective averages of residual energies of sensor nodes ($AE_r$) of each selected class interval were evaluated. Based on the result, certain categories of sensor nodes at a section of the network field indicated that the battery energy of the affected nodes was not maximally utilized thereby leading to enormous residual energy. It was concluded that the residual energy of nodes in a WSN could be optimized to extend the lifetime.*

***Keywords***: *base station, battery, lifetime, residual energy, sensor nodes*

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## I. Introduction

Wireless Sensor Networks (WSNs) is a cutting-edge technology that is making wave (rising rapidly) in contemporary times. It consists of event (parameter) to be observed, network of wireless sensors, and the event management center (Base Station or Sink). WSNs are limited in usage due to restraints in: connectivity, memory, data security, deployment, and most significantly, energy. Nodes accumulate data from the environments and transmit same to an intervening gateway or directly without any intermediary to the Base Station (BS) through wireless link [1]. In real time scenario, WSN is taking a leading role in smart homes, smart cities, surveillance systems, patient monitoring systems, military reconnaissance and a host of other applications. The battery is the principal source of energy to a sensor node and the full network of wireless sensor nodes [2]-[3]. The rate at which the energy of the battery depletes determines the lifetime of the WSN. Network lifetime is feasibly the most significant metric for estimating WSNs. It refers to the time taken before the sensor nodes become energy deficient [4].

Due to the nature of sensor node deployment in a network, renewing the battery energy of sensor nodes might pose difficulties [5]. Thus, the availability of energy is indispensable to the efficient deployment and operation of a WSN. One method to enhance the efficient use of WSN and prolong the duration of its operation is by extending the lifespan of the battery of individual sensor in a network, this will optimize the total energy of WSN. Optimal routing protocol has been developed by researchers to implement an energy efficient WSNs [6]-[7].

The energy utilization task of a wireless sensor node in a network entails; sensing of data, processing and transmission to (BS). Among these tasks, transmission of data consumes a greater share of energy. Researchers have proposed several solutions to optimally utilized energy in every unit of sensor nodes to make the most of the lifetime of the sensor arrangement [8]. Some of the clarifications include energy-aware data transmission protocol, sensing management, applying smart duty-cycle based transceivers, and the use of transceivers with low power [9]-[12]. These previous solutions reduce energy depletion meaningfully and extend the duration of the network, nevertheless, energy problem is yet to be resolved absolutely. Similarly, in a network of wireless sensors, an imbalance in the distribution of activities may consequently lead to over usage of some sensor nodes battery while others are under-utilized and in other circumstances some sensor nodes battery energy is unused. Thus, novel approaches to alleviate this problem are: To predict data transmitted in a network, to maintain a balanced load distribution in a network, and to monitor or predict the energy used in a network.

Residual or residue energy of a wireless sensor is the unused energy of the battery after the lifetime of the WSN. It changes with time and is dependent on certain factors such as ambient temperature, network topology, load distribution in a deployed network, sensor nodes location, and the Sink or BS. To address the problem of energy constraint in WSNs, diverse schemes have been proposed. These include the duty cycle scheme where wireless sensors are programmed to sleep during inactive periods, data driven scheme which centers on data routing protocols and mobility based scheme; in which wireless sensor or the BS is provided with a means for mobility. In WSN, research has established the fact that clustering of sensor nodes and hierarchical data flow to the BS significantly reduces energy utilization in a network. In clustering technique, wireless nodes are put together into unique clusters. One sensor node takes the position of a repeater between other nodes and the BS in the cluster. This node is regarded as the Cluster Head (CH) [1]. In CH selection technique, the nodes proximity to the Sink and their residual energies are considered to ensure energy conservation in WSNs [13].

According to [14], data routing techniques in WSNs being a process of data transfer from source node(s) to the terminal node or BS is a major focus in research to provide solutions to energy constraint issues militating against the distribution of nodes in a network. With the swift development of wireless sensor technology, large distribution of nodes is inevitable in the near future. Consequently, this will introduce enormous quantity of data to be processed, transmitted and received thereby creating energy constraint. Due to the fact that wireless sensor networks are fit for environment which keeps on changing, occasioned by internal or external circumstances, it is necessary to avoid the redundant restructuring of WSN. Therefore, exploring machine learning (ML) algorithms such as artificial neural network (ANN), fuzzy logic, decision tree, swarm intelligence, and reinforcement learning, which iteratively learn the properties of the environment, rapidly adapt to their behavior, and utilize the distributive nature of WSNs, can be applied in such scenario. Machine learning techniques also provide facilities that can also be applied to increase the life-span and other functionalities of WSN. Thus, ML Techniques are grand enabler for WSN that can take care of its varying nature.

## II. Literature Review

Various studies have been carried out to address energy constraint issues and it has been established that the clustering routing algorithm is one of the most efficient data routing techniques to conserve sensor node energy and extend network lifetime [15]-[16]. Several works established on cluster-based routing algorithms considered the residual energy of sensor nodes in the choice of CH.

Reference [17] suggested the early recognized clustering routing algorithm; Low Energy Adaptive Clustering Hierarchy (LEACH). The protocol prolonged the duration of WSNs and reduced the energy consumed. In LEACH, the received signal strength determines the cluster formation and CH acts as the default gateway to the Sink. Also, the nodes possess the same chance of assuming the CH position. At first, a node creates arbitrary values lying between 0 and 1 to constitute a CH by matching it with an estimated brink. Each elected CH sends a notification to non-cluster heads to constitute a cluster. Nodes that are not cluster heads choose CH which has minimum energy requirement to communicate. In general, LEACH presented an ideal model for energy consumption and provided the same likelihood for sensor node to be chosen as CH. After its election as a CH, a node cannot be re-elected in the next round. The LEACH protocol is good in its performance but not without certain limitations: It adopts one-hop communication that circumscribes its ability to scale and there is the likelihood that CHs would be concentrated in a particular section of the scheme [18].

Reference [19] developed LEACH-Centralized (LEACH-C), a novel and modified version of LEACH to surmount the inadequacies of LEACH. The Base Station decides on the eligibility of nodes to assume CHs position and form a cluster in LEACH-C algorithm. Sensor nodes send information about energy level and location to the BS. This BS evaluates the mean energy for the sensor network and excludes the sensor nodes with remnant (leftover) energy levels below the mean value to constitute the CHs for the round. In the centralized procedure, the energy load is dispersed among all sensor nodes uniformly, where the number of CHs is definite, and the network is separated into optimal and equivalent-sized cluster. Nevertheless, the creation of clumps with the same volume of sensor nodes is indefinite and it may be impossible for distant nodes from the Base Station to forward their information. Energy- LEACH (E-LEACH) protocol advances the CH selection process. E-LEACH is distributed into rounds as LEACH. The likelihood for a sensor node to be elected as CH is the same in the first round. After the first round, the residual energy of every sensor node [20] is accounted and the sensor node with higher residual energy is selected to be CH [21].

Two-level hierarchy LEACH (TL-LEACH) forwards data to the BS in one hop by CH. It involves two levels CH; main and subordinate. The merit of two-level hierarchy is the reduction in the sensor nodes that transfer information to the BS, thus, reducing the energy utilization in the network [22]. Multi-hop- LEACH (M-LEACH) protocol routes data to the BS by using a CH which makes use of another CH as a relay station. The challenge of transmission distance between CHs and BS was solved, but energy consumption during data transmission is high. New Version LEACH (V- LEACH) protocol implements a Vice-Cluster head in a cluster to assume the role of [23] a dead Cluster owing to the fact that at the death of a Cluster head, information collected will not reach its destination [21].

Reference [24] developed a Hybrid Energy-Efficient Distributed (HEED) clustering approach for ad-hoc networks [23]. CHs are randomly chosen based on their residue energy level and nodes join clusters nearest to them to reduce data communication costs. HEED extends the network lifetime and in comparison to LEACH, CHs in HEED are distributed uniformly in the network. The limitation of the HEED protocol is its inability to specify the cluster count in the respective rounds. Also, the consumption of energy is imbalanced in HEED. The problem of energy optimization is an issue being addressed in the literature. Although few works in the literature emphasize optimization techniques for residual energies but much still needs to be achieved on this subject.

Reference [25] purported an Event Driven Hierarchical Cluster based Routing protocol for event driven sensors. In this algorithm, clusters were formed geographically on the basis of uniform division of sensor node on the network area space. In the simulation environment, a certain quantity of nodes was deployed on a network field. The network structure was configured into; non-hierarchical, first level hierarchy and second level hierarchy. In each round of simulation, the average value of the residue or leftover energy rises [26] with increasing hierarchical structure. This indicated better performance of the network because sensor nodes possess enough energy in the succeeding hierarchical level. However, no optimization of the residual energies to achieve an improved network lifetime.

Reference [27] modeled energy efficient WSNs suitable for perimeter surveillance. In [27] wireless sensor nodes were grouped into non-hierarchical and other levels of hierarchical clusters. Simulations were done in MATLAB environment. Results showed that the lifetime of the networks increases as the level of the hierarchical cluster increases while the standard deviation of the network's residue energy drops as the level of the hierarchical cluster increases. However, at the completion of the network's lifetime, the residual energy of some sensor nodes was retained above the mean value which implied that the battery energy of some sensor nodes was not maximally utilized. Fig. 1 to Fig. 6 represent the histogram of the residual energy density extracted from the authors' results and modified to indicate sections of the histogram where sensor nodes' residual energy densities are above the mean value. Observations from the result showed that after the network's lifetime, a sizable volume of nodes' residual energy values were retained above the mean value.

Other works in literature studied the residue or leftover energy of sensor nodes [28] and optimization techniques to achieve energy adequacy and extend the lifetime of the WSN. Reference [29] developed a score-based load balancing algorithm such that cluster head selection was determined by nodes' residual energies. The node that possesses the greatest remnant energy assumed the position of CH. The score of the sensor node was achieved by the ratio of distance of sensor node from CH and its residue energy. The best sensor node is the node with the lowest score.

Reference [30] addressed the problem of Energy-Efficient Routing (EER) and clustering in WSNs employing Neural Network. The aim of the EER is to optimize the life-time of the network. In the method used, cluster head election was done with adaptive learning in Neural Network and after that routing and data transmission [31]. This Neural Network based algorithm was compared with existing routing protocol; LEACH, considering residual energy and number of nodes alive. EER performs better than LEACH.

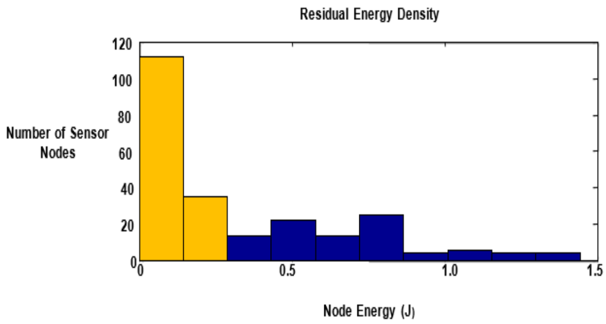


Fig. 1. Residual Energy Density of Level 1 Hierarchy

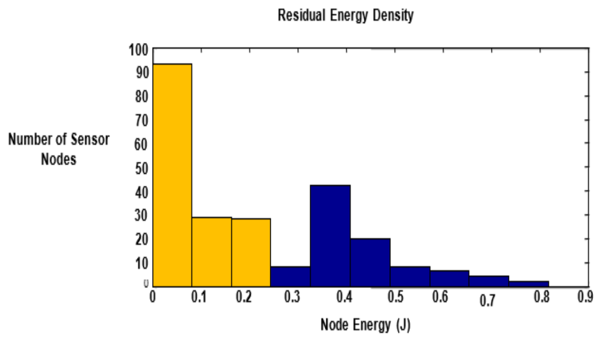


Fig. 2. Residual Energy Density of Level 2 Hierarchy

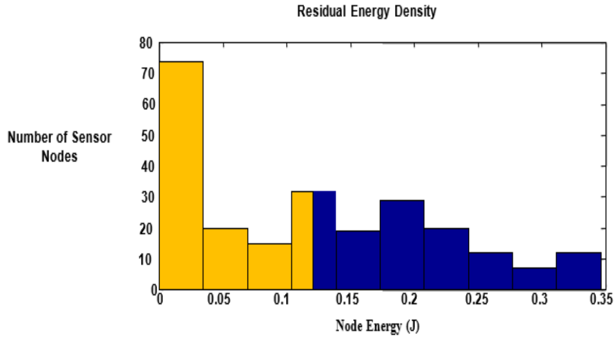


Fig. 3. Residual Energy Density of Level 3 Hierarchy

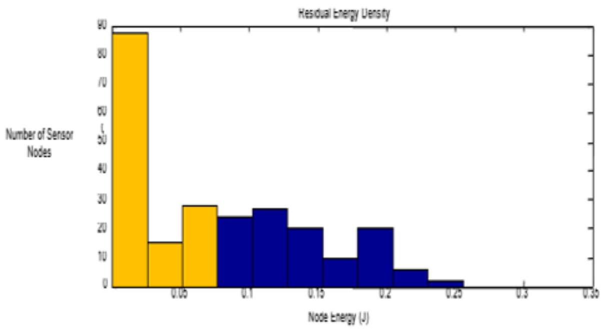


Fig. 4. Residual Energy Density of Level 4 Hierarchy

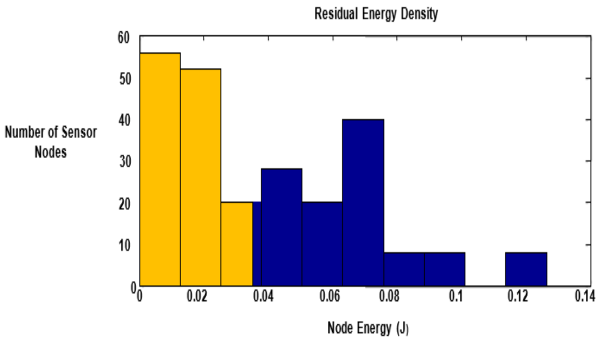


Fig. 5. Residual Energy Density of Level 5 Hierarchy

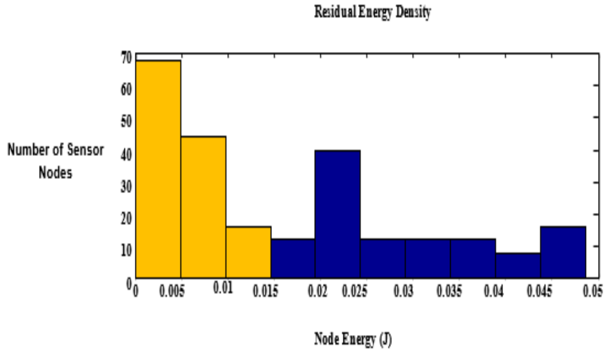


Fig. 6. Residual Energy Density of Level 6 Hierarchy

Distribution of nodes energy below the mean residual energy

Distribution of nodes energy above the mean residual energy

Reference [32] utilized Grey-Wolf Optimization (GWO) algorithm to achieve energy efficiency in wireless sensor networks. GWO scheme was used for the selection of cluster head and tree-based technique for routing. The residue energy of sensor nodes was used as a fitness parameter. The method used addressed the challenge of unequal clustering which is one of the major reasons for the early death of CHs near the BS due to heavy routing of data to the BS.

Reference [33] solved the problem related to clustering and routing by adopting a Biogeography-Based Optimization (BBO) scheme. CH was selected by utilizing BBO whose fitness function was centered on nodes' residue energy, mean distance between CH and the member nodes, and distance between CH and BS. Based on the fitness functions of residue energy and distance, an optimum route between the CH and the BS was computed with the BBO. Although the network performance was improved, the method did not decrease the maximum load of each CH and the energy consumption of the CHs was not balanced.

To resolve the problem of massive consumption of energy at the CHs which degrades the lifetime of WSNs, authors in [34] proposed a Fitness Function-based Two-Hop Routing (FFTHR) algorithm for inter-cluster routing among all the CHs of the network. The residual energy of the CHs, their relative Equlidean distances from the Base Station (BS) and their location from the centroid were considered. Based on the fitness value, a CH is identified as the Central Cluster Head which uses a one-hop to transfer data to BS while other CHs use two-hops. The simulation results reveal that the FFTHR enhances the network lifetime and saves the energy consumption of the network.

In clustering routing protocol of WSNs, CHs consume extra energy than the other nodes and thus expire earlier. Thus, the load of sensor nodes must be balanced among the CHs in order to elongate the network lifetime. Authors in [35] proposed an approximation algorithm to solve this problem with an approximation ratio of 1.1. This algorithm runs in fixed-parameter tractable time. The authors used a virtual grid infrastructure and projected a routing algorithm for the network, the routing algorithm reduces and balances the energy utilized in the network by discovering proper route between each CH and the BS.

Reference [36] addressed the problem of unequal clustering using a fuzzy-logic approach. The fuzzy logic approach was applied to reduce the interaction between the CHs and the nodes within the cluster. This approach employed the residue energy of CHs and their separations from the BS to achieve its objective.

A similar unequal clustering Algorithm is the Multi-Objective Fuzzy Clustering Algorithm (MOFCA) [35] proposed by [37]. The algorithm was proposed to balance energy utilization in WSN and advance on the fuzzy logic approach using criteria such as the remnant energies of sensor nodes, nodes distances to the BS, and density, to boost the operation efficiency of WSN. Nonetheless, the approach failed to balance the load at the CHs. Reference [38] developed a three stages algorithm. At the initial stage, clustering was done equally at all levels. In the next stage, the residue energy and the distance between a node and the BS were considered in selecting the best node to be the CH. Thereafter, distant nodes from the BS send data to the BS through the CHs while nodes near the BS transfer data directly to the BS.

Reference [39] proposed predictive models to accurately predict mobility and residue energy criteria of nodes in Mobile Wireless Sensor Network (MWSN) for effective route management. The model was simulated on an existing MWSN algorithm to evaluate its performance. The result revealed that applying this model in developing routing protocol will optimize route selection and enhance the rate of data delivery in MWSN.

Reference [40] proposed a Novel Reliable and Energy-Efficient Routing Protocol for WSNs. The research aimed to maximize the lifetime of WSN. In the method adopted, a mathematical analysis was utilized for relay nodes selection with consideration of the remnant energy and reliability. Maximum of the Minimum Residual Energy Protocol (MMREP) was thereafter proposed to select the route that makes best use of the remnant energy of its nodes subject to a reliability constraint. An entropy-like function was introduced to evaluate the homogeneity of residue energy distribution. Optimal Remaining Energy-Based Protocol (OREBP) was implemented to select the route considering the entropy of its residue energy. The lifespan increases as the number of hops rises as long as more paths are available for data routing. The implementation of entropy principle optimized the algorithm and reduced its complexity. The uniformity in energy consumption also extends WSN lifespan.

In the works reviewed in the literature, several authors considered the residual energies of sensor node as fitness metrics to determine data routing in a network. However, much is yet to be done on optimal usage of residual energy of nodes in extending the lifetime of a WSN. Detailed information about residual energy distribution in a network will enhance intelligent routing of data such as: Energy Aware Adaptive Routing protocols and ML based techniques for optimization of energy in WSNs. This work is a performance survey on the distribution of residual energies in a deployed network of wireless sensors. The enormous residual energies motivated the need to emphasize the adoption of predictive models for residual energy as a research issue to enhance network performance in relation to energy usage and network lifetime.

## III. Method Used

In the method adopted, **s**ensor nodes were uniformly dispersed on the entire boundary of the 3000 m by 50 m network field. Thereafter, a single cluster, six hierarchical clusters and eighteen hierarchical clusters of sensor node were formed based on uniform division of the perimeter of the network field. The choice of cluster head (CH) within each cluster formed was based on selection of a sensor node with minimal transmission distance to the Base Station (closest to the BS due to the fact that energy consumption is proportional to transmission distance) [28]. The CH receives information from the nodes within its cluster and transmits the received data through the most energy efficient route to the BS. Thus, to transmit an '$x$'-bit data at a distance $d$, the radio consumes energy $E_{Tx}$ (x, d). Equation (1) is the model of energy of sensor node transmitters, equation (2) is the energy model of sensor node receivers and Fig. 7 illustrates the communication model.

$$ETX\ (\mathrm{x}, d) = x * E_{TX(elec)} + x * d^2 \in_{amp} \quad (1)$$

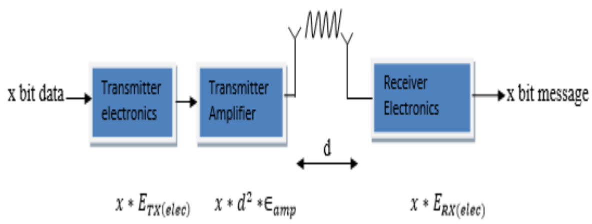


Fig. 7. Block diagram of communication model

$E_{TX\ (elect)}$ is the transmitter electronics energy, $\in_{amp}$ is the free space transmit amplifier. The radio of the receiving node transceiver expends energy $E_{RX}\ (x)$ is defined as:

$$ERX\ (x) = x * E_{RX(elect)} \quad (2)$$

$x$ is the size of received data in bits and $E_{RX(elect)}$ is the energy requirement of receiver electronics. At the start of data transmission, different energy assessments were carried out to decide on the sensor node to be selected as the subsequent CH; this is centered on sensor node closest to the BS and with maximum energy $E_{sn}$ (max) within the cluster at the moment of data transmission.

$$E_{sn}(\max) = E_{in} - (\epsilon_{amp} * x * d_n^{\ 2}) \tag{3}$$

$E_{in}$ is the initial energy of sensor node prior to data transmission, the parameters in the parenthesis evaluate the energy expended in the course of data transmission where $\epsilon_{amp}$ is the transmitter amplifier energy, $x$ is the size of data and $d_n$ is the distance between sensor nodes. The cluster sizes considered were one, six and eighteen clusters. A comparison of the various hierarchical scenarios was carried out for the experimental dimension in MATLAB. Table I is a list of parameters for simulation. The values of the mean residue energy (MRE) and respective averages of residual energies of sensor nodes ($AE_r$) above the MRE values were taken on a class interval of 50's of the sensor node identity (nid).

$$AEr = \frac{\sum E_r}{50} \quad \text{where } E_r > MRE \tag{4}$$

$E_r$ denotes residue energy of individual node. Sensor nodes batteries energies retained above the mean residual energy after the network lifetime are considered to be under-utilized. Fig. 8 illustrates the flowchart of the performance survey.

TABLE I
SIMULATION PARAMETERS AND QUANTITIES

| Parameters | Quantities |
|---|---|
| Initial sensor node energy | 10 Joules |
| Size of data (x) | 2000 bits |
| Data period | 1 Second |
| Network Field Dimension | 3000m by 50m |
| Transmitter electronic energy | 50 nJ/bits |
| Receiver electronic energy | 50 nJ/bits |
| Transmitter power amplifier energy | 100 pJ/bits/m$^2$ |

## IV. Results Discussion

The results of simulation in MATLAB are illustrated with bar graphs in Fig. 9 to Fig. 11. The Mean Residual Energy (MRE) defines the mean value of the unused energy of sensor node battery in the entire network while the Average Residual Energy $AE_r$ is estimated on a class interval of 50 of the sensor node identities for residual energies ($E_r$) > MRE.

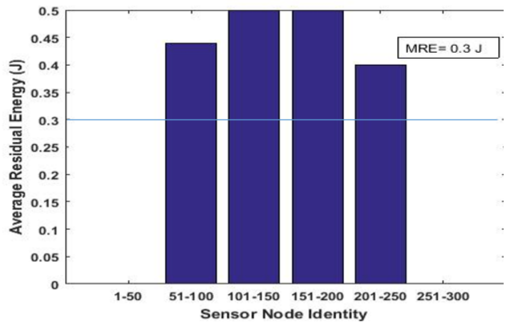


Fig. 9. Average Residual Energy $AE_r$ of Sensor nodes for Single Cluster Network

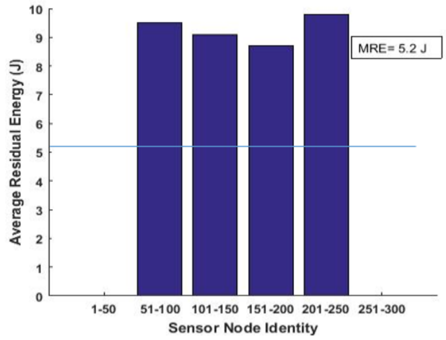


Fig. 10. Average Residual Energy $AE_r$ of Sensor nodes for Six Cluster Network

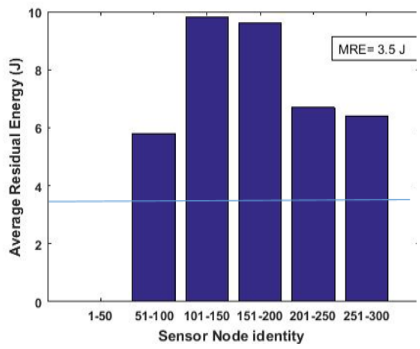


Fig. 11. Average Residual Energy $AE_r$ of Sensor nodes for Eighteen Cluster Network

Fig. 9 illustrates the distribution of residual energy in a single cluster network. The Mean Residual Energy (MRE) after the lifetime of the network is 0.3 J (3% of the initial energy of nodes). Only sensor nodes identified as (1-50) and (251-300) have 0 Joules of energy remaining while the average of other sets of sensor nodes is above the value of MRE. Fig. 10 is the result of six cluster networks. The MRE is 5.2 J (52% of the initial nodes

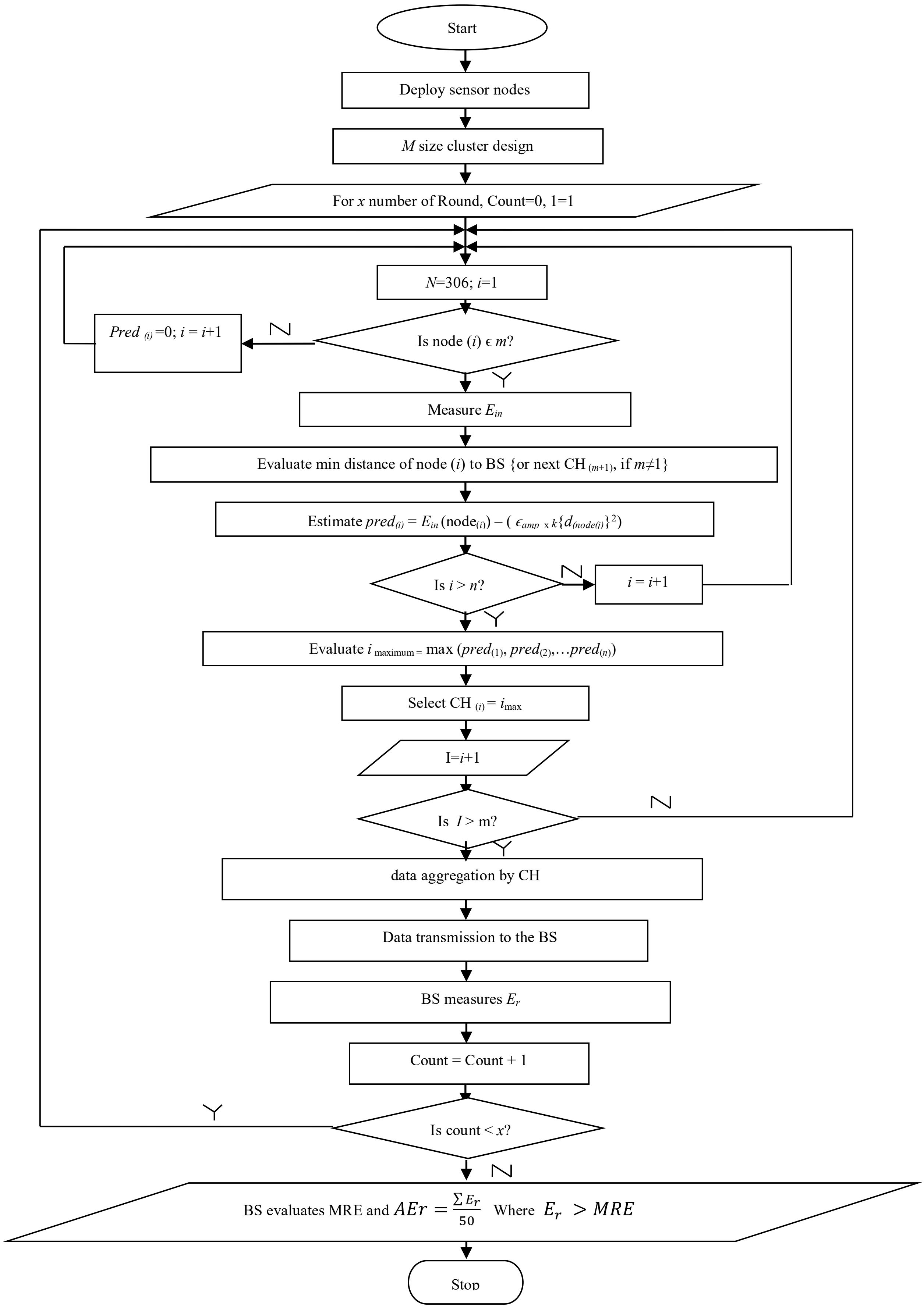


Fig. 8. Flowchart of the performance survey

energy) and similar to Fig. 9, sensor nodes identified as (1-50) and (251-300) have 0 Joules of energy remaining while the average of other sets of sensor nodes is above the MRE value. Similarly, the average residual energy of these groups of sensor nodes is closer to the initial value of the energy of sensor nodes (10 Joules). Fig. 11 is the result of eighteen cluster networks, only the nodes identified as (1-50) have 0 Joules as average residual energy while the averages of other categories of sensor node are above the MRE value of 3.5 J (35% of initial nodes energy). The extremely under-utilized battery energy exists among sensor nodes identified as (101-150) and (151-200) where the average residual energy is close to the value of initial energy of sensor nodes; 10 Joules. The values of the mean residue energies (MREs) at the end of the network lifetime are 3%, 52%, and 35% of the initial node energy for single cluster, six hierarchical clusters and eighteen hierarchical clusters respectively. Thus, a consideration of the challenges associated with non-maximal usage of energy in WSNs occasioned by the enormous residue energy of some sensor nodes may necessitate the need for energy prediction models to optimize the network energy and elongate the lifetime of the network.

## V. Conclusion

The major constraint of the wireless sensor nodes is the battery energy. Though the energy available in the battery of sensor nodes is important, but the mean residue energy of the nodes that constitute the entire WSN could play a vital role in extending the lifetime of the network. Based on the performance survey executed in this work, a substantial Joule of sensor node energy was under-utilized at the end of the lifetime of the 0WSN. The under-utilized energy of sensor node battery in a network is regarded as residual energy that may as well be concentrated at a particular area within the network field. In the previous research work, residual energies were used as a fitness parameter to determine the most efficient route to the BS. However, based on the performance survey carried out in this research, sufficient research work is needed to optimally utilize the residual energies to extend the lifetime of WSNs. A good prediction model; essentially, Machine Learning based prediction models can accurately predict energy consumption and the allocation of residual energy in a network. Adopting this will enable network programmer to re-route data through appropriate path in the network and strategize a means to optimize energy usage so as to extend the lifetime of WSN.

## Conflict of Interest

The authors announce no conflict of interest in the publication process of the research article.

## Authors Contributions

Author 1: Conceptualization, literature review, simulation, original draft preparation, and typesetting; Author 2: Idea formulation, literature review, analysis, and editing; Author 3: Supervision, editorial work, and review; Author 4: Review, editorial work, and investigation; Author 5: Editorial work, review, and writing.

## References

[1] A. Lipare, D. R. Edla, and V. Kuppili, "Energy efficient load balancing approach for avoiding energy hole problem in WSN using Grey Wolf Optimizer with novel fitness function," *Applied Soft Computing Journal* 84, 2019, doi: 10.1016/j.asoc.2019.105706.

[2] R. Yarinezhad and S. Y. Hashemi, "Solving the load balanced clustering and routing problems in WSNs with an fpt-approximation algorithm and a grid," *Pervasive and Mobile Computing 58,* (2019), doi: 10.1016/j.pmcj.2019.101033.

[3] O. J. Odeyinka, M. C. Ndinechi, O. C. Nosiri, and N. C. Onuekwusi, "A Survey on Energy Hole in Clustering Routing Protocol of Wireless Sensor Networks" *Journal of Asian Scientific Research,* vol. 10, no. 2, pp. 59-69. 2020, doi: 10.18488/journal.2.2020.102.59.69.

[4] X. Tang and J. Xu. "Optimizing Lifetime for Continuous Data Aggregation With Precision Guarantees in wireless sensor networks," *IEEE/ACM Transactions on Networking (TON),* vol. 16, no. 4, pp. 904–917, 2008.

[5] V. V. Krishnamoorthy, "Energy aware routing technique based on Markov model in wireless sensor network," *International Journal of Computers and Applications*, 2017.

[6] T. Amgoth and P. K. Jana, "Energy-aware routing algorithm for wireless sensor networks," *Computer and Electrical Engineering,* vol 41, pp. 357-367. 2015.

[7] Y. H. Lin, Z. T. Chou, C. W. Yu, and R. H. Jan, "Optimal and Maximized Configurable Power Saving Protocol for Corona-Based Wireless Sensor Networks," IEEE Transaction on Mobile Computing, vol. 14, no. 12, pp. 2544-2559. 2015.

[8] A. I. Al-sulaifanie, B. K. Al-sulaifanie, and S. Biswas, "Recent trends in clustering algorithms for wireless sensor networks: A comprehensive review," *Computer Communications,* vol. 191, no. 395-424. 2022, doi: 10.1016/j.comcom.2022.05.006.

[9] A. A. Abbasi and M. Younis. "A Survey on Clustering Algorithms for Wireless Sensor Networks," *Computer Communications*, vol. 30, no. 14-15, pp. 2826-2841. 2007, doi: 10.1016/j.comcom.2007.05.024.

[10] M. M. Afsar and N. M-H. Tajarani, "Clustering in Sensor Networks: A Literature Survey," *Journal of Networks and Computing Application,* vol. 46, pp. 198-226. 2014, doi:10.1016/j.nca.2014.09.005.

[11] S. Verma, N. Sood, and A. K. Sharma, "Genetic Algorithm-Based Optimized Cluster Head Selection for Single and Multiple Data Sink in Heterogeneous Wireless Sensor Network," *Applied Soft Computing,* vol. 85. 2019, doi: 10.1016/j.asoc.2019.105788.

[12] S. Doostali and S. M. Babamir, "An Energy Efficient Cluster Head Selection Approach for Performance Improvement in Network-Coding-Based Wireless Sensor Networks with Multi-Sinks," *Computer Communications,* vol. 164, pp. 188-200. 2020, doi: 10.1016/j.comcom.2020.10.014.

[13] O. J. Odeyinka, O. A. Ajibola, M. C. Ndinechi, O. C. Nosiri, and N. C. Onuekwusi, "A Review on Conservation of Energy in Wireless Sensor Networks," *International Journal of Smart Sensor Technologies and applications (IJSSTA),* vol. 1, Issue 2, April - June 2020.

[14] K. M. Noh and J. S. Park, "Data Transmission Direction Based Routing Algorithm for Improving network Performance of IoT

Systems," *Applied Science*. vol. 10, pp. 3784. 2020, doi: 10.3390/app10113784.

[15]S. A. Nikolidakis, D. Kandris, D. D. Vergados, and C. Douligeris, "Energy efficient routing in wireless sensor networks through balanced clustering algorithms," vol. 6, pp. 29-42. 2023, doi: 10.3390/a6010029.

[16]G. R. Asha and Gowrishankar, "Energy efficient clustering and routing in wireless sensor networks," *Procedia Computer science*, vol. 134, pp. 178-185. 2018.

[17]W. R. Heinzelman, A. Chandrakasan, and H. Balakrishan, "Energy-efficient communication protocol for wireless micro sensor networks," *In proceedings of the 33rd Hawaii International Conference on System Sciences,* 2000, pp. 1-10.

[18]J. N. Al-karaki and A. E. Kamal. "Routing techniques in wireless sensor networks: A Survey," *IEEE Wireless Communication,* vol. 11, no. 6-28. 2005, doi: 10.1109/MWC.

[19]W. B. Heinzelman, A. Chandrakasan, and H. Balakrishan, "An application - specific protocol Architecture for wireless micro sensor networks," *.IEEE Transactions on Wireless Communications,* vol. 1, no. 4, pp. 660-670. 2004, doi: 10.1109/TWC.

[20]S. K. Singh, P. Kumar, and J. P. Singh, "A Survey on Successors of LEACH Protocol," *IEEE Access,* 2007.

[21]F. Xiangning, S. Yulin, M. B. Yassein, Y. Bani, and A. Khamayseh, "Improvement on LEACH protocol for Wireless SensorNetwork (V-LEACH)," *International Journal of Digital Content Technology and its Applications,* vol. *3*, no. 2, pp. 132-136. 2009, doi: 10.1109/Sensorcomm.

[22]Fanian and M. K. Rafsanjani, "Cluster-based routing protocols in Fakhrosadat wireless sensor networks: A survey based on methodology" *Journal of Network and Computer Applications.* 2019.

[23]A. P. Speer and I-R. Chen, "On Optimal Path and Source Redundancy for Achieving QoS and Maximizing Lifetime of Query-Based Wireless Sensor Networks" *14th IEEE International Symposium on Modeling, Analysis, and Simulation.* 2006.

[24]O. Younis, and S. Fahmy, "A hybrid energy- efficient distributed clustering approach for Ad-hoc sensor networks," *IEEE Trans. Mobile Computing*, vol. 3, pp. 366 -379. 2004, doi: 10.1109/TMC.2004.41

[25]S. Taruna, and R. T. Megha, "Event Driven Hierarchical Cluster based routing protocol for Wireless sensor network," *International Journal of Advanced Research in Computer Science and Software Engineering,*vol. 3, no. 4, pp. 549-556. 2013.

[26]S. A. El-said, A. Osamaa, and A. E. Hassanien, "Optimized hierarchical routing technique for wireless sensors networks," *Soft Computing.* 2015.

[27]A. L. Imoize, O. A. Ajibola, T. R. Oyedare, J. O. Ogbebor, and S. O. Ajose, "Development of an Energy-Efficient Wireless Sensor Network Model for Perimeter Surveillance," *International Journal of Electrical Engineering and Applied Sciences (IJEEAS),* vol. 4, no. 1. Apr. 2021.

[28]P. Maheshwari, A. K. Sharma, and K. Verma, "Energy Efficient Cluster based Routing Protocol for WSN using Butterfly Optimization Algorithm and Ant Colony Optimization," *Ad Hoc Networks.* 2020.

[29]V. S. Gattani, and S. M. H. Jafri, "Data collection using score based load balancing algorithm in wireless sensor networks," in: 2016 International Conference on Computing Technologies and Intelligent Data Engineering (ICCTIDE'16), IEEE, Kovilpatti, India, 2016, pp. 1–3, 2016, doi:10.1109/ICCTIDE.2016.7725323.

[30]N. Kumar, M. Kumar, and R. B. Patel, "Neural Networks based Energy Efficient Clustering and Routing in Wireless Sensor Networks," *First International Conference on Networks and Communication* pp. 34-39. 2009.

[31]N. K. Nehra, M. Kumar, and R. B. Patel,. "Neural Network Based Energy Efficient Clustering and Routing in Wireless Sensor Networks," *First International Conference on Networks & Communications.* 2009.

[32]N. A. Al-Aboody, and H. S. Al-Raweshidy, "Grey wolf optimization-based energy- efficient routing protocol for heterogeneous wireless sensor networks," in: 2016 4th International Symposium on Computational and Business Intelligence (ISCBI), IEEE, Olten, Switzerland, 2016, pp. 101–107. 2016, doi: 10.1109/ISCBI.2016.7743266.

[33]P. Lalwani, H. Banka, and C. Kumar, "A Biogeography-based Energy Saving Routing Architecture for Wireless Sensor Networks," *Soft Computing* vol. 22, no. 5, pp. 1651-1667. 2018.

[34]A. Panchal and R. K. Singh, "FFTHR: Fitness Function based Two-Hop Routing in WSN," *Internet Technology Letters.* 2020.

[35]R. Yarinezhad and S. N. Hashemi, "Solving the load balanced clustering and routing problems in WSNs with an fpt- approximation algorithm and a grid structure," *Pervasive and Mobile Computing.* 2019.

[36]H. Bagci and A. Yazici, "An energy aware fuzzy approach to unequal clustering in wireless sensor networks," *Applied Soft Computing,* vol. 13, no. 4, pp. 1741-1749. 2013.

[37]S. A. Sert, H. Bagci, and A. Yazici, "Multi-objective fuzzy clustering algorithm (MOFCA) for wireless sensor networks Application," *Soft Comput.,* vol. 30, no. 2015, pp. 151–165. 2015, doi: 10.1016/J.ASOC.

[38]P. M. Salehi and M. Abbaszadeh, "Proposing a method to solve energy hole problem in wireless sensor networks," Alexandria Eng. *J.,* vol. 57, no. 3, pp. 1585–1590. 2018, doi: 10.1016/J.AEJ.2017.05.012.

[39]O. O. Olakanmi, K. O. Odeyemi, and A. Abbas, "Mobility and energy prediction models: Approach toward effective route management in mobile wireless sensor networks," *Engineering Reports 2020,* 2019, doi: 10.1002/eng2.12095

[40]A. Mohammed and L. Janos. "Novel Reliable and Energy-Efficient Routing Protocol for Wireless Sensor Networks," *Journal of Sensor and Actuator Networks,* vol. 9, no. 5, pp. 1-13. 2020.