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Energy Efficient Node Selection Algorithm (EENSA) in Routing Protocols of Wireless Sensor Networks



Abstract: The sensor node with finite energy becomes the main constraint for operation of wireless sensor networks (WSNs). Researchers proposed routing protocols that use little energy for dealing the constraint. We suggest an Energy-Efficient Node Selection Algorithm (EENSA) that increases the network's overall lifespan. The node's trust level, connectivity degree, and distance from the sink is analyzed individually and combined linearly by assigning weights to each parameter. It provides node's effective potential function that makes it an energy efficient node. Rounds needed to choose the most energy-efficient node is also conformed. EENSA comparison with traditional method using energy distance for routing protocols like Power Efficient Gathering in Sensor Information Systems (PEGASIS), Shortest Hop Routing (SHORT), Optimized Reduced Energy Consumption (OREC), and Load Balance and Energy Efficient Routing Algorithm (LBEERA) is done through simulation. There is significant extended 8% improvement in network lifetime using EENSA which carries the energy efficient node selection.

Keywords: Wireless Sensor Networks (WSN), Shortest Hop Routing (SHORT), Optimized Reduced Energy Consumption (OREC), Energy Efficient Node Selection Algorithm (EENSA), Load Balance and Energy Efficient Routing Algorithm (LBEERA)

1. Introduction

A wireless sensor network (WSN) is basically an autonomously-configured wireless network that lacks a fixed infrastructure. Its primary purpose is to observe and record various physical situations within an environment, by storing the data collected in central repository. WSNs have garnered significant interest of people due to their cost-effectiveness, compact size, and versatility, making them applicable across a multitude of fields, including healthcare, military operations, and underwater monitoring [1, 2, 3]. More recently, the advancements in WSN technologies for devices, networks, and data managements have found new applications in areas like smart factories, having strategically positioned sensor nodes to gather essential information concerning machinery and products, optimizing operations of smart factory. Additionally, WSNs can be effectively deployed in smart cities, to establish a platform for public and municipal workers, with an efficient service delivery enhancing the management of city resources for optimal efficiency. In WSN, across a wide geographical area numerous sensor nodes are strategically distributed for gathering observational data that is afterwards transmitted to centrally located base station or server or sink. The sink is usually positioned far away from the individual sensor source nodes transmission range. So for the extensive coverage area, multi-hop transmission is required to be employed. This necessitates computation of most efficient route by intermediary gathering sensor nodes to relay collected data to the distant sink. One of the foremost challenges in the effective deployment of WSNs is energy efficiency [4, 5, 6]. Sensor nodes operate on limited energy reserves and are often not easily rechargeable once deployed. Moreover, since a significant portion of their energy is consumed by the radio communication device, it becomes imperative to design energy-efficient routing algorithms. Ongoing research in the realm of energy-aware routing primarily focuses on achieving two key objectives: total energy consumption minimizing along the routing path and ensuring a relatively uniform distribution of residual energy among nodes [7, 8]. To attain these objectives, routing strategies for WSNs often opt for paths with the shortest distance among nodes or the fewest hops. This choice is made based on the understanding that the overall energy consumption is straight influenced by distance between nodes and total intermediate nodes that are transmitting data. Consequently, the routing algorithms aim to optimize these factors, thereby prolonging the network operational lifespan and reliability.

In [9], Ding et al. have given the machine learning based energy efficient routing algorithms for wireless sensor networks. For WSN, to ensure the effective management of energy-constrained nodes while maintaining delivery of high-quality data to intended recipients, several algorithms and protocols have been developed [10, 11, 12]. Clustering is one of prominent strategy employed for energy consumption reduction in WSNs. This involves grouping the data collected, either through clustering or fusion techniques, to generate additional meaningful information before forwarding it to the end-user [13, 14]. This approach offers the potential for extending lifespan of network, enhancing its scalability, while simultaneously providing fault tolerance and load balancing.

An IRPL routing protocol is proposed by Zhang et al. in [15] to satisfy the energy balance requirements of WSN. This routing protocol presents a model with new routing topology control by dividing communication area into equal area rings. Heinzelman et al. [16, 17] developed Low Energy Adaptive Clustering Hierarchical (LEACH) which is one of the earliest hierarchical clustering protocols designed to conserve WSN energy and prolong its lifetime. In LEACH, sensor

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nodes are prearranged with two-tier hierarchy, where every node can either serve as Member Node (CM) or Cluster Head (CH). There is periodic interchanges of roles of CMs and CHs in the network, normally denoted as a "round". A single CH manages several CM nodes in each cluster. Data is collected and transmitted by CM nodes to their corresponding CHs to aggregate and subsequently transmit to the sink. However, it's worth noting that in LEACH, the selection of CHs does not consider the sensor node's residual energy (RE) levels. Thus, selected CH may have a risk of possessing insufficient energy to efficiently transfer the collected data to the sink [19, 20]. This restriction highlights the necessity for extra enhancements in CH selection ensuring utilization of energy more efficiently within network. Prashanth et al. in [18] present cluster based routing protocol for heterogeneous wireless sensor networks. They provide insights into the construction, maintenance and operation of WSN in detail. Generally various surveys focus on simulations and controlled conditions, whereas this survey focuses on true implementations and practical deployments. Researchers have developed a multitude of energy-efficient clustering algorithms to address this critical constraint [13, 14, 19, 20] and load-balancing routing protocols [21, 22, 23], aimed at mitigating the consumption of energy and prolonging the WSNs operational lifespan. The energy-efficient nodes selection for routing protocols and the designation of cluster heads that are routing data to the sink play pivotal roles in enhancing the longevity of a network. It is crucial to make these selections wisely, as inappropriate choices can result for a substantial decrease in energy efficiency. Numerous approaches have delved into the selection of energy-efficient cluster heads. These studies predominantly employ fuzzy-based clustering techniques [11, 12]. However, it's noteworthy that their applicability to routing protocols such as SHORT, PEGASIS, OREC, LBEERA, among others, has not been thoroughly explored. In addition to factors like connectivity and distance, sensor node trust levels should also be given due consideration when devising an energy-efficient node selection algorithm. Trustworthiness can be a critical aspect in assuring the effectiveness and reliability of the selected nodes for various tasks within the network.

This paper is introducing a novel Energy Efficient Node Selection Algorithm (EENSA) that helps in enhancing the energy efficiency of selecting node within routing protocols, improving the performance and longevity of WSN. The determination of a node's potential to become an energy-efficient node involves a separate analysis of individual parameters. The proposed EENSA based routing scheme endeavors to bridge an essential gap by introducing the concept of trust into the design of energy-efficient node selection algorithms. In the node selection process, this novel approach seeks to incorporate trustworthiness as a critical factor thereby further advancing the effectiveness and reliability of energy management strategies within wireless sensor networks. We derive mathematical expressions to quantify this potential, taking into account the sink to node distance, its connectivity degree, and its trust level. To obtain the overall potential of a node as an energy-efficient candidate, we linearly combine these parameters. The complete selection protocol is constructed using this EENSA algorithm as its foundation. We conduct a comparative analysis with an energy-distance-based efficient node selection algorithm across various routing algorithms to validate the effectiveness of EENSA. This comparative study allows us to assess the efficiency of our proposed routing algorithm in comparison to existing approaches. The key contributions of the research work in this paper are:

- 1) Energy-efficient node selection algorithm (EENSA) designed for integration with routing protocols is proposed. The key objective of the designed EENSA is to identify nodes with the potential to operate efficiently in terms of energy consumption. We have derived a mathematical model to quantify this potential, taking into account several key parameters such as node's proximity to the sink, its connectivity degree within the network, and node's trust level that contribute to a node's suitability as an energy-efficient candidate.
- 2) In addition, the proposed EENSA algorithm have incorporated node's proximity to the sink, its connectivity degree within the network, and node's trust level parameters alongside the remaining energy of each node to ensure balanced data load distribution among the identified energy-efficient nodes.
- 3) For the performance assessment of our EENSA algorithm, we employed a comparison metric based on number of successful data transfer rounds to sink. Importantly, a round is considered successful only when unambiguous packets reach the sink; rounds involving selfish nodes that transmit ambiguous packets leading to network energy reduction are not deemed successful. While our proposed scheme primarily focuses on transfer of data in centralized way, it can be adapted for distributed data transfer scenarios, such as those found in protocols like OREC and LBEERA, where multiple energy-efficient nodes contribute to the network's overall efficiency. The proposed approach is also compared with existing energy efficient algorithms such as PEGASIS, OREC, SHORT, and LEEBRA in the context of network lifetime for four different sets of values of α , β , and γ .

The paper is arranged in following manner: Related work in field and its overview is given in section-2. In section-3, we introduce the design of our energy-efficient node selection protocol, outlining its application to various parameters. Section-4 presents the algorithm that is constructed based on the design principles outlined in section-3. The section-5 presents the results of our simulation experiments, offering insights into the proposed EENSA performance. Lastly, in section-6, the paper is concluded with the key findings and contributions of the research.

2. Related Work

Routing in WSNs is essential for ensuring reliable transfer of data, minimizing latency, and promoting energy-efficient process. Wireless communication, while indispensable for data transmission from sensor nodes to sink nodes, consumes a significant amount of power, which poses a critical challenge since most sensor nodes rely on batteries for their energy supply [10, 11]. In wireless networks, employed Sensor nodes typically possess limited computational capabilities and lack comprehensive knowledge of the network's topology. Consequently, calculating the optimal route to a destination quickly becomes a complex task for individual nodes. Even when a node manages to ascertain an optimal routing path,

it may not stay optimal over time because of different environmental factors, such as node mobility, unstable wireless channel conditions, and sensor nodes with dynamic energy status. Traditional ad hoc routing protocols are broadly categorized as two classes: reactive and proactive protocols [24, 25, 26]. In reactive routing protocols, routes are calculated only when they are required, and routes are stored solely by sensor nodes for their immediate neighbors. Although this strategy minimizes routing table maintenance overhead, it may introduce latency in the delivery of sensed data when routes need to be established on demand. In contrast, in proactive routing even when routes are not immediately needed, there is pre-computation of routes and these routes are stored in routing tables at each node. This approach, while ensuring readily available routes, imposes substantial routing table maintenance overhead, limiting the routing protocol scalability. To address these challenges, ongoing research efforts are dedicated to finding optimal routing paths with minimal energy consumption, aiming to strike a balance between energy efficiency, latency, and scalability in WSNs [10, 17, 23].

Mohemed et al. [27] have tackled the challenge of addressing network "holes" in Wireless Sensor Networks through the development of two energy-efficient, distributed, and connectivity-aware routing protocols. These protocols are employed differently in local and global environments, effectively reducing the need for frequent topology reconfiguration and thereby extending the overall network lifespan. Khan et al. [28] focused on the challenge with mobility of sensor node within Wireless Body Area Sensor Networks. Given the dynamic nature of human activities, the human body positioned sensor nodes frequently change their locations. This dynamic movement can lead to packet loss and energy inefficiencies when static routing algorithms are employed. The authors tackled this issue by devising a dynamic routing algorithm that takes into account factors like the nodes residual energy, sink distance hop count, and throughput while selecting the node for next hop for data forwarding. Razaque et al. [29] introduced an innovative protocol called P-LEACH, which combines the strengths of Power-Efficient Gathering in Sensor Information Systems (PEGASIS) and Low Energy Adaptive-Clustering Hierarchy (LEACH). P-LEACH aims to enhance performance with addressing limitations of static routing in PEGASIS and cluster-based routing in LEACH, resulting in an improved routing approach. Baker et al. [30] introduced the GreeAODV routing protocol in the context of Vehicular Ad Hoc Networks (VANETs), which incorporates the routing protocol GreeDi into the Ad Hoc On-Demand Distance Vector (AODV) protocol. This integration aims in achieving energy-efficient routing, particularly for the next hop selection. They demonstrated the effectiveness of their approach in city map-based VANET scenarios, showing improvements over AODV. An energy-efficient routing protocol designed for Flying Ad Hoc Networks (FANETs) named "Energy Connectivity-Aware Data Delivery" is proposed by Oubbati et al. [31]. Their protocol ensures connectivity by utilizing information about unmanned aerial vehicles (UAVs), including their location and speed. This information helps for packet loss minimizing that may result from the UAVs movement, improving the overall efficiency of data delivery in such networks.

Several studies have explored strategies for aggregation of maximum data and network lifespan in WSNs. Ardakani et al. [32] introduced an efficient-routing algorithm that prioritizes data aggregation. In this approach, mobile agents receive sensor nodes data, aggregate it, and then transfer the aggregated data towards sink. In routing protocols, this strategy helps to mitigate issues such as packet loss and delay by leveraging the mobile agents' movement patterns. In [33], the authors shown the trade-off amongst effective data aggregation with minimizing total link cost. Routing strategy with weighted data aggregation is introduced to find a balance between these objectives. By optimizing the node routes within a clustered WSN, they enhanced data aggregation effectiveness and extended the network's overall lifespan. For reducing transmitted data volume over wireless multimedia sensor networks Yazici et al. [34] introduced a fusion-based framework through intra-node processing. In this the sensor node is equipped with machine learning techniques to detect objects, enhancing accuracy while simultaneously decreasing the data load. This framework not only conserves energy but also optimizes data transmission efficiency. Haseeb et al. [35] focused on addressing security concerns when applying traditional routing algorithms for large-scale Internet of Things (IoT) environments. This secure protocol is "light-weight structure-based data aggregation routing" that utilizes in-route data aggregation within traditional routing protocols. This approach enhances both the security and efficiency of data routing in IoT networks.

El Alami et al. [36] introduced an algorithm which is LEACH-based and selects fuzzy cluster heads. This algorithm utilizes a membership function that incorporates elements like residual energy, expected efficiency, and proximity to sink to determine a chance value. For a given round, nodes with greater chance values are chosen as Cluster Heads (CHs). This approach aims to improve CH selection in WSNs, considering multiple factors for better energy efficiency. For determining estimated output membership functions, Sert et al. [37] introduced Modified Clonal Selection Algorithm, improving the rule-based fuzzy routing performance. Fuzzy logic is employed for handling scenarios where cluster boundaries are ambiguous or unclear. The researchers derived optimal solutions through initial membership functions and iterative experiments, contributing to more efficient and adaptable routing strategies in WSNs. Lee et al. [38] enhanced LEACH algorithm for mobile sensor networks by incorporating fuzzy logic. They address challenges arising from node mobility by considering factors like residual energy, node movement speed, and pause time in a membership function. By calculating chance values based on this function, the algorithm optimizes the selection of CH nodes. This approach helps mitigate packet losses caused by node mobility. El Alami et al. [39] presented an energy-efficient approach called Enhanced Clustering Hierarchy (ECH) that incorporates a sleep-wake up mechanism for neighboring and overlapping nodes of WSNs. By minimizing data redundancy, the lifetime of network is extended. This strategy optimizes energy utilization and reduces unnecessary data transmission.

Indeed, much of the research in energy-efficient node selection has traditionally been centered around the selection of cluster heads, often within protocols like LEACH in the literature [19, 20, 29]. However, the proposed research

addresses an important gap by introducing the concept of trust into the energy-efficient node selection algorithm design. By incorporating trust as a parameter in the selection process, the proposed algorithm goes beyond the conventional focus on cluster head selection and takes a step towards more comprehensive and robust energy efficiency in WSNs. Trust plays pivotal role in ensuring the effectiveness and reliability of selected nodes, that has a major influence on the overall performance and longevity of WSNs. This innovative proposed approach broadens the scope of energy-efficient node selection and has the potential to contribute significantly to the field by addressing a critical aspect that has been previously overlooked in many research works.

3. Design Methodology for proposed Energy Efficient Node Selection Algorithm (EENSA)

Identifying and focusing on the three crucial parameters—Node-to-Sink Distance, Node Degree, and Node Trust Level—represents a thoughtful and systematic approach to protocol design for energy-efficient node selection. By individually analyzing the dependency of energy-efficient node selection on each of these parameters, our protocol algorithm EENSA can offer a more nuanced and tailored solution for enhancing the overall efficiency and performance of WSNs. This comprehensive consideration of these parameters allows for a more fine-grained control and optimization of node selection, which is likely to result in improved network longevity and energy utilization. Let's discuss above three key parameters in detail.

3.1. Node to Sink distance

In wireless sensor networks (WSNs), the relationship between the dissipated energy by an efficient node and sink to node distance is a critical aspect for energy efficiency optimization. While it is commonly presumed that energy dissipation is inversely proportional to the squared distance from the sink. In our experimental setup, a square grid topology is employed with nodes positioned at 10m grid intervals as shown in Figure 1. Each node in the network is designated as an energy-efficient node for 100 of data transfer rounds using the SHORT protocol [40]. For every node acting as an energy-efficient node, the energy consumption of entire network is computed. Remarkably, our findings, as shown in Figure 2, suggest a departure from the expected inverse square relationship. Instead, the results indicate that nodes located at distances between the nearest and farthest nodes from the sink tend to transfer data more energy efficiently when selected as the efficient node. This observation challenges the conventional assumption of a strict inverse square relationship between node distance from the base station and its potential for being an efficient node. This research provides a deeper understanding of the complex dynamics at play in WSNs, highlighting the need for more nuanced approaches to energy-efficient node selection that take into account real-world conditions and network characteristics.

For deriving the distance dependence metric, we take two dimensional arrangement having nodes shown as different points relative to X and Y axis. For the node to be an efficient node, we need to check value of potential metric for that node. This metric considers parameters like node to sink proximity and its role in data transfer, enabling a more informed and precise selection of energy-efficient nodes within the network. By incorporating distance-related metrics into our analysis, we can better tailor our node selection algorithm to the unique characteristics and requirements of our WSN setup. For instance node i potential metric $P_{ed}(i, t)$ for a round t w.r.t. node's distance from the sink can be given as:

$$P_{ed}(i, t) = \frac{1}{(x_i - x_1 - \lambda_1 x_2)^2 + (y_i - y_1 - \lambda_2 y_2)^2 + k^2} \quad (1)$$

Where,

(x_1, y_1) - represents the co-ordinate of the sink,

(x_2, y_2) - shows the central point co-ordinate of the square grid topology,

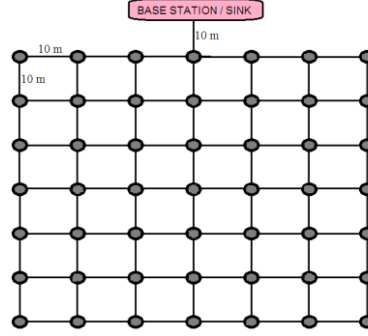
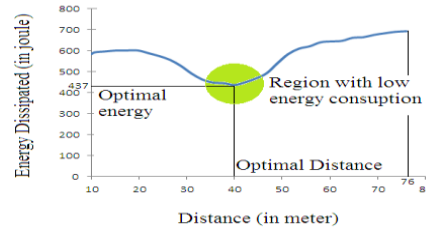
(x_i, y_i) - represents i th node co-ordinate of square grid arrangement with $i = 1, 2, \dots, N$ (here total network nodes is N).

λ_1 and λ_2 are weights on (x_2, y_2) coordinate and is calculated by putting individually $(x_i - x_1 - \lambda_1 x_2)^2$ and $(y_i - y_1 - \lambda_2 y_2)^2$ to 0. The reason is when a node located in arrangement (if live) is central point of the arrangement then P_{ed} metric should be highest for corresponding node as $\frac{1}{k^2}$.

Hence $\lambda_1 = \frac{(x_i - x_1)}{x_2}$ and $\lambda_2 = \frac{(y_i - y_1)}{y_2}$. The value of k is considered as $\sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$ means it is sink to central point of the arrangement distance. Thus potential metric has the largest value as $P_{edmax} = \frac{1}{k^2}$.

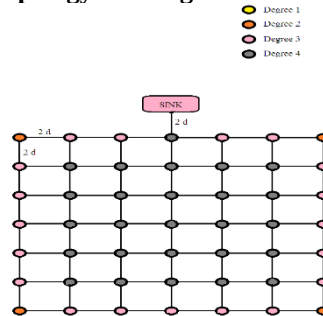
The parameter $P_{ed}(i, t)$ is then normalized w.r.t. P_{ed} of all remaining network nodes. The normalized parameter is indicated as $W_D(i, t)$ given by Equation (2) as given below

$$W_D(i, t) = \frac{P_{ed}(i, t)}{\sum_{j=1}^N P_{ed}(j, t)} \quad (2)$$

Figure 1 Connectivity in Square grid topology**Figure 2 Dissipated energy per node versus efficient node distance from sink**

3.2. Node's connectivity Degree

The node's connectivity degree, denoted as (i, t) , indeed has a significant part in describing network's energy efficiency, particularly for efficient node selection. Our consideration of the data packet size received by a node as a determinant of energy dissipation is a valid and practical approach. A node with a high degree of connectivity may experience substantial energy drain after each data transfer round. This is due to the increased energy dissipated for handling a larger number of data packets received. Whereas, an efficient node having lower connectivity degree may lead to increased energy dissipation in the network, as some packets may need to be relayed through longer routes (possibly involving two or more hops) rather than being directly delivered to an efficient node. To quantify this dependency between connectivity degree and energy efficiency is very crucial aspect in analyzing any routing algorithm. By analyzing and interpreting this dependency, one can gain valuable insights about how different degrees of node connectivity impact energy dissipation within the network. This approach allows us to tailor node selection based on the network's specific connectivity characteristics, ultimately optimizing energy efficiency in WSN. In this research work the nodes are positioned at equal intervals of $2d$ from one another as shown in Figure 3. Each node is assigned a unique node ID represented by ' i ,' where ' i ' varies from 1 to . To create the connectivity of shown graph based on this arrangement and determine the connectivity value for each node, denoted as $k(i, t)$, a maximum transmission distance of $\frac{5d}{2}$ is considered.

Figure 3 Square grid topology showing each node connectivity degree

The network's average energy consumption is calculated for every node in the topology, during data transfer to a sink node for 100 rounds via the most efficient node, as shown in Table I. Power calculations are performed following the guidelines outlined in reference [41], and routing is facilitated using the SHORT [40] protocol. Table 1 provides information on degrees of the nodes (k) and the average energy dissipation of these nodes within the network.

Table 1 Network average energy dissipation versus node's degree

$k(i,t)$	Average Energy Dissipation (joules)
1	49.7
2	43.7
3	44.4
4	48.4

Based on the experimental observations a relation can be defined for the i th node, its degree $k(i, t)$ and nodes potential for being an efficient node $P_{en}(i, t)$ by Equation (3).

$$P_{en}(i, t) = \frac{1}{\left(\left(k(i, t) - \frac{\max(k(i, t)) + \min(k(i, t))}{2} \right)^2 + \frac{\max(k(i, t)) + \min(k(i, t))}{2} \right)} \quad (3)$$

The above equation is normalized w.r.t. the sum of P_{en} values. And connectivity degree dependence parameter shown as $W_N(i, t)$ can be expressed as

$$W_N(i, t) = \frac{P_{en}(i, t)}{\sum_{i=1}^N P_{en}(i, t)} \quad (4)$$

The node's connectivity degree potential parameter should assign more potential to nodes having connectivity which is arithmetic mean of maximum degree and minimum degree nodes. Above Equation assigns potential that will be maximum as

$$P_{enmax} = \frac{1}{\frac{\max(k(i, t)) + \min(k(i, t))}{2}} \quad (5)$$

3.3. Node's Trust level

A selfish node can significantly impact the system energy efficiency by causing repeated retransfer of similar packets to the sink because of either receiving wrong or no acknowledgment for the initial request. This repetitive transmission and potential packet duplication place additional strain on the network and can lead to a wasteful consumption of energy resources. We compute the trust metric for any node i denoted by $P_t(i, t)$ from [42]. The trust dependence is given with normalized parameter $W_T(i, t)$ by the Equation (6) as

$$W_T(i, t) = \frac{P_t(i, t)}{\sum_{i=1}^N P_t(i, t)} \quad (6)$$

4. Proposed Energy Efficient Node Selection Algorithm (EENSA)

To establish a relationship for a node's effective potential to become an efficient node, the parameters W_D , W_N and W_T are combined, taking into account their dependencies. These parameters are linearly superimposed using separate weights α for W_D , β for W_N and γ for W_T appended with each parameter. In this approach each individual parameter operates independently, and it's possible that one parameter holds higher priority than the others in determining a node's efficiency. Therefore, the node's resultant potential $W(i, t)$ making it an efficient node is given by

$$W(i, t) = \{\alpha W_D(i, t) + \beta W_N(i, t) + \gamma W_T(i, t)\} \times E(i, t) \quad (7)$$

Here, $E(i, t)$ gives i th node energy at an instant introduced for distributing the efficient nodes throughout the arrangement and give relief to any specific node to be efficient node each time occurring fast depletion of energy. The rule $\alpha + \beta + \gamma = 1$ and $(\alpha, \beta, \gamma > 0)$ is followed by the linear combination parameters. For relaxing the sink from efficient node calculation at every data transfer round we predict for the total rounds to be completed after which new efficient node selection occurs. An array $K = [k_1, k_2, k_3, \dots, k_n]$ is prepared whose i th element corresponding to the current efficient node is zero and other elements k_j gives the rounds required for the node j to become an efficient node when i th node is acting as an efficient node.

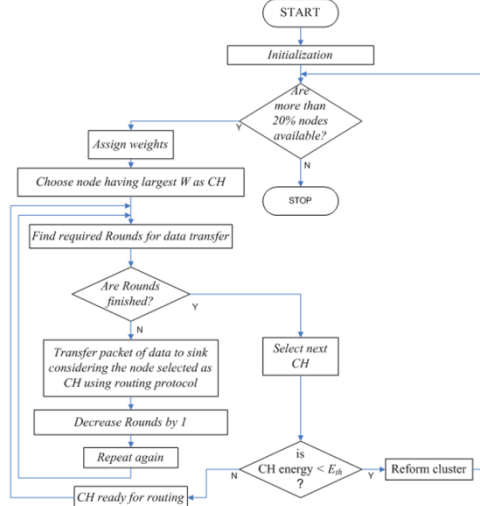
From the node i placed at particular distance to sink, the energy required for a packet transfer is calculated using as energy communication model described in [38] and given as $E_{transfer}(i, t)$. Required energy for remaining all nodes is computed using the transmission distance for the packet at time t as $E_{transfer}(j, t)$. The array elements k_j are obtained as the rounds required for an efficient node i to reduce its potential and becoming equal to node j when the i th efficient node is chosen at time instant t represented as below.

$$\left(E(i, t) - k_j E_{transfer}(i, t) \right) \times \frac{W(i, t)}{E(i, t)} = \left(E(j, t) - k_j E_{transfer}(j, t) \right) \times \frac{W(j, t)}{E(j, t)} \quad (8)$$

For every element, k_j value of the $K - k_i$ array is given by:

$$k_j = \frac{W(i, t) - W(j, t)}{\left(E_{transfer}(i, t) \times \frac{W(i, t)}{E(i, t)} \right) - \left(E_{transfer}(j, t) \times \frac{W(j, t)}{E(j, t)} \right)} \quad (9)$$

The Figure 4 illustrate the detailed flow chart for our proposed energy efficient node selection strategy.

Figure 4 Square grid topology showing each node connectivity degree

For the proposed Energy Efficient Node Selection Algorithm (EENSA), Pseudo code is given below. Lower value of $K - k_i$ shows required rounds of data transfer for new selection of efficient node. The parameters W_D and W_N are computed when there is a network arrangement change (i.e. if the node death in the network occurs). W_T is obtained at each instant whenever efficient node selection is carried out for including the dynamics of trust of the nodes. It is assumed that the network gets dysfunctional after death of 80% of the nodes. Due to polynomial time solvable algorithm, there is no need for approximation algorithm. Given E_{th} is the smallest energy that makes a node dysfunctional.

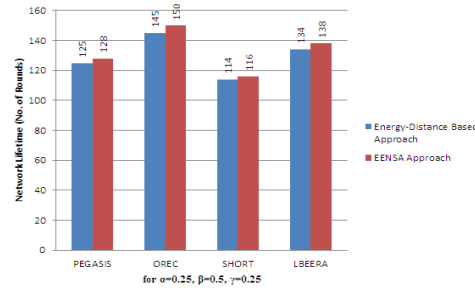
Algorithm 1. EENSA Pseudo code:

Data: topology of network, number of nodes n , each node's initial energy, data packet length, α , β and γ
Output: efficient node selected and rounds required favoring selected node (requiredrounds) as efficient node.
Initialization: $K, W_D, W_N, W_T = n \times 1$ elements of 0, $repeat=0$, $recalculate=0$, $effnode=0$.

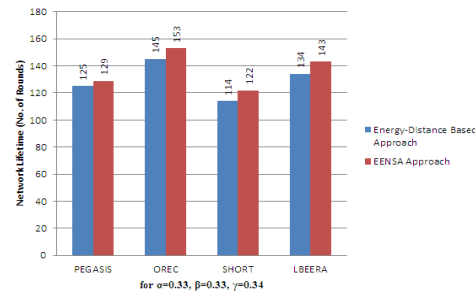
Calculate W_D, W_N, W_T for total network nodes at $repeat=0$;
While Minimum 20% of total nodes of network are available **do**
 $recalculate=0$;
 Choose node having largest W as $effnode$;
 Calculate $requiredrounds = \min(K - k_{effnode})$;
 while $requiredrounds > 0$ **do**
 Transfer packet of data to sink considering the node selected as $effnode$ using routing protocol;
 $requiredrounds = requiredrounds - 1$;
 $repeat = repeat + 1$;
 end
 for $s = 1:n$ **do**
 if $E(i, repeat) < E_{th}$ **then**
 $E(i, repeat) = 0$;
 set $recalculate = 1$;
 end
 end
 if $recalculate$ **then**
 Recalculate W_D, W_N ;
 end
 Recompute W_T ;
end

5. Discussion on Results

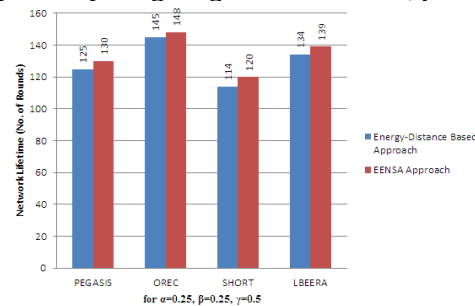
As depicted in Figure 1 in section 3, a square grid topology is employed with nodes positioned at $10m$ grid intervals. Length of each packet considered as $200bits$. Total of 100 nodes are assumed to be present in the considered network. Each node is initially assumed to be endowed with $500mJ$ of energy. A threshold energy level (E_{th}) is set at $10mJ$. MATLAB 8.2 on core $i3$ with $1.3GHz$ CPU and $4GB$ RAM is employed for simulation purpose. Using four routing protocols, the simulation is conducted: PEGASIS, LBEERA, SHORT, and OREC. An energy-efficient node selection process, outlined in EENSA Algorithm, is implemented, employing various linear combination parameters. Figure 5 to Figure 8 provide a comparison between the traditional energy-distance dependent efficient node selection algorithm and proposed EENSA across different routing protocols. Various values of linear combinations are assigned during the comparison. For comparison, the rounds of data transfer (representing network lifetime) is used as a metric leading to 80% depletion of the nodes within the network.

Figure 5 Graph Comparing weight values $\alpha=0.25, \beta=0.5, \gamma=0.25$ 

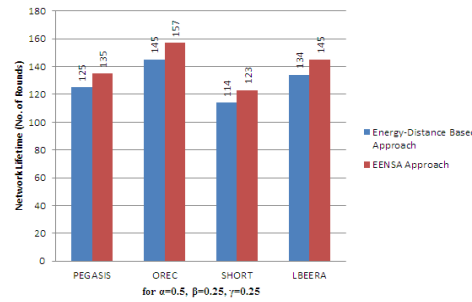
As observed from Figure 5, for the values $\alpha = 0.25, \beta = 0.5, \gamma = 0.25$ EENSA approach lasts till 128 rounds for PEGASIS in comparison with 125 rounds showing 2.4% increase in lifetime. For OREC EENSA approach lasts till 150 rounds in comparison with 145 rounds showing 3.4% increase in lifetime. For SHORT EENSA approach lasts till 116 rounds in comparison with 114 rounds showing 1.7% increase in lifetime. Similarly, EENSA approach lasts till 138 rounds for LBEERA in comparison with 134 rounds showing 2.9% increase in lifetime. Results for the another values $\alpha = 0.33, \beta = 0.33, \gamma = 0.34$ EENSA approach lasts till 129 rounds for PEGASIS in comparison with 125 rounds showing 3.2% increase in lifetime. For OREC EENSA approach lasts till 153 rounds in comparison with 145 rounds showing 5.5% increase in lifetime. For SHORT EENSA approach lasts till 122 rounds in comparison with 114 rounds showing 7% increase in lifetime. Similarly, EENSA approach lasts till 143 rounds for LBEERA in comparison with 134 rounds showing 6.7% increase in lifetime. These results are represented in Figure 6.

Figure 6 Graph Comparing weight values $\alpha=0.33, \beta=0.33, \gamma=0.34$ 

Also in results compared for the values $\alpha = 0.25, \beta = 0.25, \gamma = 0.50$ EENSA approach lasts till 130 rounds for PEGASIS in comparison with 125 rounds showing 4% increase in lifetime. For OREC EENSA approach lasts till 148 rounds in comparison with 145 rounds showing 2% increase in lifetime. For SHORT EENSA approach lasts till 120 rounds in comparison with 114 rounds showing 5.2% increase in lifetime. Similarly, EENSA approach lasts till 139 rounds for LBEERA in comparison with 134 rounds showing 3.7% increase in lifetime. These results can be observed in Figure 7.

Figure 7 Graph Comparing weight values $\alpha=0.25, \beta=0.25, \gamma=0.50$ 

Comparison using values $\alpha = 0.5, \beta = 0.25, \gamma = 0.25$ shows that EENSA approach lasts till 135 rounds for PEGASIS in comparison with 125 rounds showing 8% increase in lifetime. For OREC EENSA approach lasts till 157 rounds in comparison with 145 rounds showing 8.2% increase in lifetime. For SHORT EENSA approach lasts till 123 rounds in comparison with 114 rounds showing 7.9% increase in lifetime. Similarly, EENSA approach lasts till 145 rounds for LBEERA in comparison with 134 rounds showing 8.2% increase in lifetime. This is depicted in Figure 8.

Figure 8 Graph Comparing weight values $\alpha=0.50$, $\beta=0.25$, $\gamma=0.25$ 

Throughout all the conducted experiments, there is a noticeable improvement in network lifetime. However, it's remarkable that when α , representing the potential w.r.t. node to sink distance is increased, the lifetime of network increases by more than 8% for different routing protocols, as observed in Figure 7. On the other hand, when a higher weight is assigned for β , in network lifetime the smallest increase is observed. This suggests that the energy-efficient node selection protocol little dependent on the node's connectivity degree. It's important to mention that this article does not address the linear combination value optimization for different routing protocols. Different routing protocols may indeed benefit from distinct linear combination optimal values. This aspect has been considered as a potential area for future research and optimization efforts.

6. Conclusion and Future scope

This paper presents design of a novel Energy Efficient Node Selection Algorithm (EENSA). It is designed for the energy-efficient nodes selection and its comparison with the traditional energy-distance dependent efficient node selection for routing protocols is done. Linearly combined three parameters: a node's distance from sink, node's connectivity degree and node's trust level combined with node's instantaneous energy depict the node's potential to be an energy-efficient node. Different α , β and γ parameter combination values result in variations of network lifetime. When α (combination value) assigned to potential parameter showing node distance (W_D) is kept higher, maximum network lifetime increase is observed. In remaining cases considered, the proposed EENSA outperforms the traditional energy-distance dependent algorithm for node selection. In the future we are going to focus on fine-tuning of α , β and γ parameter using a suitable optimization technique taking into account various network conditions. We believe that this will definitely ensure enhancement in network lifetime of WSN.

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Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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