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METHODS

Efficient Energy Mechanism in Heterogeneous WSNs for Underground Mining Monitoring Applications

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ABSTRACT Wireless Sensor Networks (WSNs) play an important role in underground mining applications. In particular, they help to collect information using sensors and provide monitoring of complex mine environments to avoid potential risks and manage operations. Despite the importance of WSNs, they face the problem of energy consumption and the difficulty of replacing the batteries of the sensor nodes. The distributed energy-efficient aggregation protocol (DEECP) helps to reduce the power consumption of the WSN. This protocol enables an increase in the lifetime of a WSN. The DEECP algorithm uses the clustering concept and selects cluster heads (CHs) according to the election probability based on the ratio between the residual energy and network average energy of each node. However, this method does not provide an optimum solution because it does not take into account the different sensor energy levels. In addition, the algorithm does not consider the effect of the distance between the base station and sensor node likely be chosen to become a CH. This can significantly affect the performance of the WSN. This paper proposes an optimization threshold for CH selection based on three energy levels of a sensor, namely, low, high, and super as well as the measurement of the distances between base stations and possible nodes to be selected as CHs to optimize the CH selection method. The proposed approach is evaluated and compared with DEECP in terms of dead nodes, alive nodes, and network throughput. The results show that the proposed approach outperforms DEECPs in terms of network stability and lifetime.

INDEX TERMS Underground mining, silver mines, WSNs, energy efficiency, clustering topology, DEECP, distance awareness.

I. INTRODUCTION

A WSN consists of many sensor nodes that have limited energy, report the sensed data and exchange information with the base stations (BS). Due to the limited energies of the sensor nodes, WSNs require a mechanism to increase the lifetime of the network by reducing the energy consumption of the nodes. Different protocols have been designed to overcome energy efficiency issues in homogenous WSNs. However, underground mine WSNs have been considered to be heterogeneous because such WSNs can deploy different types of sensors with different energy characteristics [1].

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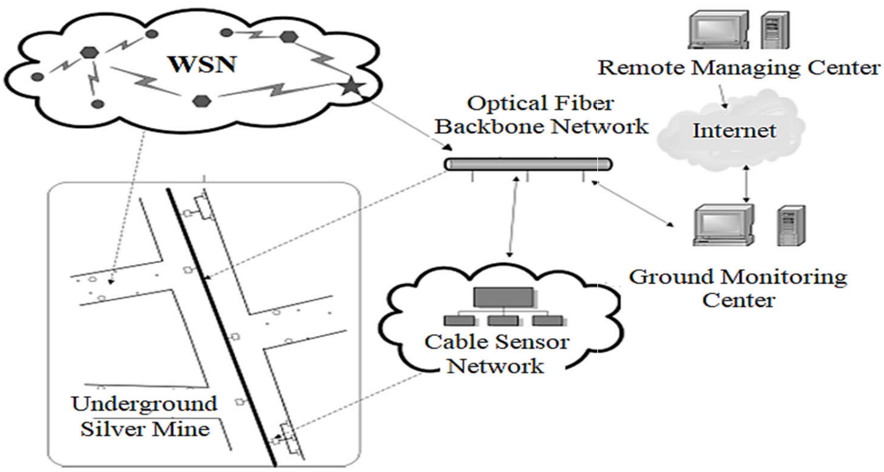


FIGURE 1. Ad-Hoc WSN for underground silver mine monitoring application.

In critical applications, WSNs are very useful for monitoring and control. Specifically in underground silver mining applications, processes can be linked to communications, as is the case in other industrial applications [2].

The underground mining industry often experiences loss of human life and infrastructure due to accidents, where using WSN monitoring can reduce such risks. Underground mine production can become risky due to the mine's environments and conditions. An example of an underground mining application is a silver mine environment. The continuous monitoring of hazards in such mines is essential to ensure safety and high productivity, and WSNs are often used in such mines including the silver mines in Saudi Arabia. In such a WSN, sensors are used to monitor many mine environmental risks related to vibrations, temperature, and air concentration. However, due to the long-term nature of WSN operations in silver mine applications, their energy consumption can degrade the performance of monitoring operations [3]. To reduce WSN energy consumption, clustering-based energy-efficient protocols can be used to reduce power consumption and enhance network operation. Accordingly, this study provides an energy efficiency clustering-based protocol for the deployment of underground silver mine monitoring applications.

WSN technologies such as UWB and ZigBee are considered for underground mines. Table 1 summarizes the properties of WSN technologies for mine applications [4]. Bluetooth has limited network capacity and communication distance ability. Hence it is not suitable for underground mine communications which require communication over large distances.

Wi-Fi also cannot be used because of its high power consumption [5]. ZigBee technology is considered more suitable for WSN mine communications because it has more positive impacts than the previous technologies in terms of energy consumption, appropriate distance for communications, and network capacity [6].

TABLE 1. WSNs technologies used in underground mine applications.

Features	Wi-Fi	Bluetooth	ZigBee	UWB
Frequency Range	2.4, 5 GHz	2.4 GHz	2.4 GHz	3, 10 GHz
Distance Coverage	20 to 100 m	10 m	50 to 500 m	Less than 10 m
Network Capacity	32 nodes	7 nodes	More than 65000 nodes	10 to 500 nodes
Data Rate	11 Mbps	1 Mbps	0.25 Mbps	100 to 500 Mbps
Power Consumption	500 to 1000 mW	1 to 100 mW	20 to 40 mW	30 mW
Complexity	High	High	Low	Medium

Proper communication within mines and between underground work areas and surface monitoring stations will enable better underground facility operations. In particular, the communication ability in underground mines provides many services related to safety, production, and productivity; in addition, it facilitates the daily monitoring operations, extraction of products, and their transportation to the

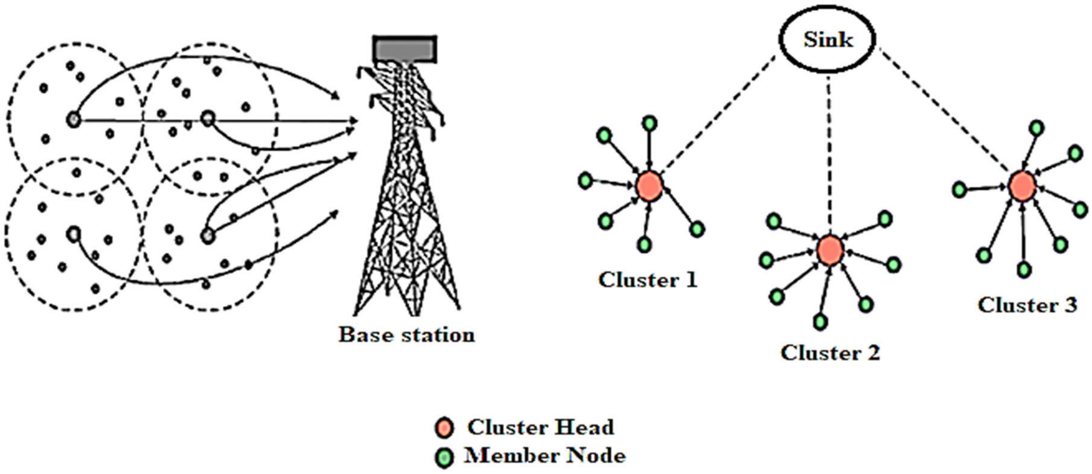


FIGURE 2. WSN-based cluster heads approach.

surface [3]. Thus the WSNs for silver mine monitoring, as shown in Figure 1, will provide technical support to monitor and control silver mining operations.

In underground mine WSNs, hundreds of sensor nodes are deployed randomly in the mine environment [7]. These nodes send data to the base station through the gateway link. The WSN nodes have limited power and their batteries cannot be recharged or replaced [8]. Moreover, nodes located in a position far from the base station cannot be directly communicated with since this will require high energy. This leads to the concept of node clustering by which sensor nodes in the cluster can communicate with the selected cluster head (CH).

Clustering-based protocols enable groups of sensor nodes to be close to each other and the cluster heads act as gateway route nodes [10].

These protocols are known as hierarchical clustering protocols, where the clusters and the cluster heads (CHs) of the clusters are created. The CHs have the responsibility to collect data from their respective groups and then pass the data to the base station. Data aggregation in distribution centers significantly reduces the network power consumption by reducing the total number of data messages exchanged between the senders and base station [11].

The idea behind the energy efficiency-based clustering approach in WSNs is that nodes are bound to send their data directly to a specified number of selected CHs (see Figure 2).

Therefore, the network cannot transfer the traffic between the different nodes and the base station with high efficiency except by using CHs [11]. However, CHs must be properly configured depending on the network parameters to ensure that energy consumption is significantly reduced.

The distributed energy-efficient clustering protocol (DEECP) is a clustering-based mechanism that estimates the WSN network average energy to perform the cluster head selection. In DEECP, the selection probability of a CH depends on the normal and advanced nodes. The idea is that nodes with more residual energy are more likely to be a CH [11]. However, this approach may not result in proper CH selection in the case of underground mine applications because due to the mine environment shape, the nodes with the highest energy can be in positions far from the base station.

Thus, the clustering mechanism will be affected by the long communication distance, causing the network to lose more energy. Therefore, the CH selection must be aware of the node's distance from the base station while ensuring that they have the largest amount of energy. The DEECP strategy works to distribute energy consumption effectively on the WSN network [12].

However, in the case of the diversity of node types and the multiplicity of their energies, there could be an advanced node with the same energy as the normal nodes. This can lead to the death of several advanced nodes faster when the DEECP protocol is used.

In this paper, we present an improved DEECP technique based on a distance-aware approach with more efficiency in defining the cluster head election probability. The proposed cluster head selection mechanism enables enhancement of the overall WSN performance in the case of energy level heterogeneity of sensors. From the simulation results, the proposed mechanism shows better performance in heterogeneous WSN mine applications in comparison to the DEECP.

It gives the best performance in terms of stability and lifetime. Further research can be performed to consider the dynamic channel properties and fading challenges in underground mine environment applications.

The rest of this paper is organized as follows; Section II reviews the most recent related works, which is concerned with enhancing the energy consumption in WSN for both homogeneous and heterogeneous, by focusing on improving the mechanism for CH election in clustering approaches in addition to provides the motivation and contribution of the proposed study. In section III, the underground WSN technical background has been reviewed. The methodology of the proposed study is presented in section IV, which shows the underground mine application model, the proposed mechanism and the evaluation metrics used during analyzing the enhanced mechanism. In section V, the simulation results and discussion was reviewed, and finally, the paper is concluded by section VI.

II. RELATED WORK AND MOTIVATION

Recently, many studies related to underground WSNs have appeared for evaluating sensor nodes in mine environment applications. Most studies are focused on the ability of WSNs to have a long lifetime due to the problems of sensor nodes' power consumption. The following related works that were published between 2017 and 2021 are chosen because of their contributions to underground mines' WSN energy efficiency.

In [12], the authors propose a comprehensive integrated system that integrates all WSN aspects, such as signal propagation, protocols, and energy control. The study addresses three WSN design considerations for underground mine environments. The authors review the WSN propagation modeling and energy-efficient communication protocol used with ZigBee and DASH-7. Moreover, they compare ZigBee and DASH-7 operations at a lower frequency and evaluate the energy efficiency in underground mines. They also provide measurements for hybrid communication protocols that improve energy efficiency. The study also introduces an algorithm that detects interconnected events to improve the reliability of disaster detection.

Authors in [13] review a method to design a monitoring system for underground mine environments by considering the use of ZigBee technology. The study evaluates the parameters of both underground and network environments for ZigBee network construction. The model is analyzed to ensure that the network can perform various monitoring applications related to the readings of humidity and temperature, in addition to controlling ventilation in the underground mine environment.

The proposed model by the authors provides a general assessment of the monitoring and communication systems for underground mine applications. This allows the extraction of the technical and economic requirements for such networks.

In [14], an energy-efficient free topology model based on a random walk strategy is developed. The authors classify the network into several clusters and use a random walk strategy to select the cluster heads. They then evaluate the network model and observe the simulation results. The proposed model shows high flexibility in the event of random failure and can extend the life of the network by balancing the remaining power of the nodes.

In [15], the authors provide an optimization method for gas monitoring in underground coal mines based on WSN. Their methodology addresses two aspects, namely, reducing deployment costs and increasing the life of WSNs. The authors review the proposed approach in two phases, first by assuming that the users provide the minimum lifetime required according to the mining schedule that needs to be optimized for reducing deployment costs. This means that the WSN design has fewer nodes to meet the required lifetime constraint.

In the second phase, to achieve network optimization, the configuration is rearranged to extend the lifetimes of the nodes. The authors test the proposed method, and the results meet the requirements of sensing ability for mine areas with minimum cost, in addition to guaranteeing maximum network lifetime.

The study in [16] uses a Finer Force Care-up (FFC) method, which enables sharing of the remaining energy between the sensor nodes in underground sensor networks. The method is dedicated to grid networks based on distance calculation between the sink nodes and the neighbor nodes using the Monte-Carlo-Localization (MCL) method. This method enables the sink node to collect the remaining energy from the neighbor nodes and calculate the energy-draining caused by each packet transfer in the network. FFCs can improve the lifetime of underground sensor networks, increase the packet delivery ratio and speed, and share the remaining energy without deploying additional wired and wireless devices.

In [17], the authors present a route optimization problem for a WSN for underground mine localization and monitoring. The study focuses on how to adapt network routes to transmit the data with a high-energy performance. The method calculates the quality of service (QoS) to provide a better strategy for an energy-efficient routing mechanism. In this study, the authors review an algorithm that takes into account the movement of nodes as well as the propagation characteristics of the underground mine channel.

The algorithm assumes that at least one path exists between the sending and receiving nodes. It then calculates the quality of service and optimizes the bit error rate. The authors in [18] present a method to evaluate the energy of all nodes in multipath WSNs. In this method, a routing schedule is prepared at the BS, which shares the information with each of the axes in the whole network. Through the analysis of the proposed network, the results show that the multipath network offers several benefits, as the communication between the sender and the receiver is improved through hops.

Authors in [19] present many studies related to process control systems for underground applications. In particular, the study is concerned with clarifying the processes related to data transfer and processing in monitoring systems that use WSNs. The paper presents some methods that depend on implementing smart monitoring systems and reviews the challenges they face in terms of accuracy, information exchange, and integration of data from several sources as well as early detection mechanisms.

This study shows that the new methods, such as using artificial neural network (ANN) technology for data fusion and emergency classifications to monitor underground operations, have a good monitoring effect. In the study presented in [20], the authors propose a new intelligent routing protocol to enhance the network lifetime and ensure efficient energy during routing operations. The energy-efficient routing protocol depends on the fuzzy rules mechanism to make routing decisions. The proposed protocol is compared with the equalized cluster head election protocol and shows better performance.

In [21], the problems related to coal mines in terms of the narrow and complex work environment as well as the obstacles faced by the monitoring system in the sensor networks, and their defects in terms of energy consumption and budget are studied. Furthermore, a mechanism is introduced to spread the sensors evenly in the narrow tunnels inside the mine, in addition to adjusting the volume of data exchanged according to energy consumption and dynamically balancing it between the sensor nodes. The proposed forwarding algorithm gives higher performance compared to conventional algorithms, achieves a significantly longer network life cycle, and ensures optimal node energy utilization.

In [22], [23], it is shown how to collect data from distributed IoT nodes based on a WSN in a specific region. The researchers present two problems related to clustering and routing in large-scale IoT-based WSNs and then develop a new clustering-based routing protocol to jointly solve both of these issues. The protocol selects the cluster headers in a way that provides anti-fail routing and then finds an appropriate routing path based on the minimum number of hops based on the availability of alternative routing paths. The analysis of the proposed protocol shows that it improves the lifetime of the network and the management of nodes with high efficiency.

In [24], the authors demonstrate a hybrid algorithm to reduce power consumption by using the cluster head selection approach in a WSN. The algorithm depends on a mechanism known as Sparrow Search that works to enhance the nodes' lifetime by knowing the vital capabilities of the live nodes and dead nodes with the possibility of investigating the remaining energy and productivity and then using a detailed model to choose the CHs. Through the analysis, it is found that the proposed algorithm gives better performance than other algorithms, such as LEACH, LEACH ABC, and TABU_PSO.

In [25], the authors propose an enhanced energy-efficient clustering mechanism that depends on the electrostatic discharge approach. This enables the implementation of a fully connected network with the shortest path between the nodes and the cluster head (CH). The mechanism is evaluated in a multi-hop environment and shows high performance in terms of network lifetime. This approach is also able to fully make the connection between sensor nodes with an efficient energy strategy. The results show that the proposed mechanism reduces the number of dead nodes and enhances packet delivery when compared to the LEACH, LEACH-C, BO-LEACH, and ESD protocols.

In [26], the authors introduce an enhanced heterogeneous gateway-based multi-host routing (HMGEAR) protocol that helps to reduce the power consumption of distant nodes. The protocol works on selecting the cluster heads based on the remaining energy with the use of a multi-hop communication mechanism throughout the network, in addition to the use of energy holes elimination. The results of the analysis show that the adopted mechanism gives better results compared to the MGEAR and SEP protocols.

III. MOTIVATION

Different algorithms have been recently proposed for improving energy efficiency and lifetime for WSNs used for underground mine monitoring. However, because of sensor heterogeneity in mine applications, different energy levels need to be considered for the senses used in such networks. Most algorithms however consider homogenous WSNs and consequently assume that all nodes have the same energy levels.

Some studies have developed algorithms for heterogeneous WSNs by considering the sensor energy level variation. However, methods of ensuring efficient energy consumption and reliability are lacking, especially for heterogeneous WSNs in underground mine applications. Accordingly, the main objective of this paper is to discuss and evaluate the challenge of energy efficiency in underground WSN-based IoT since it is the most important issue influencing the stability and lifetime of the networks.

In this study, we enhanced one of the most effective energy-clustering algorithms and enhance the mechanism of cluster head selection by calculating the probability of nodes becoming a cluster head according to the sensor energy levels and positions of the nodes relative to the base station (distance aware approach). This provides a stable WSN and increases the pet's work lifetime and throughput.

A. CONTRIBUTIONS

We propose an energy-efficient distance-aware clustering approach by enhancing the DEECP mechanism to optimize CH selection. Our method is based on sensor energy levels and distance measurements. The major contributions of this paper are as follows:

- An efficient clustering protocol for underground mines' WSN network is developed which enables efficient selection of the CHs for inter-cluster multi-hop routing.
- A mechanism is proposed to overcome the challenges related to the cluster topology, the cluster size and the distribution of the energy consumption. The main concept concerns the distances of nodes in clusters from the base station. Nodes that are close to the base station are likely to be elected as CHs for communication exchanges.
- An enhanced protocol is proposed that enables the selection of CHs for multi-hop mode among CHs to reduce nodes' energy consumption. Consequently, this leads to the reduction of the number of dead nodes and increases the network lifetime.
- The proposed protocol is evaluated and compared with the DEECP protocol. The results show that the proposed protocol gives much better performance than DEECP.

TABLE 2. Summary of energy efficiency studies in WSN for underground mines applications.

Approach	Feature	Advantage	Citation
Energy tradeoff and autonomous event detection in mines WSN	Energy-efficient hybrid communication protocol using DASH-7	Suitable detection mechanism and acceptable energy latency	Umar et al., 2017 [12]
Monitoring model for underground mine environments using ZigBee WSN	Testing system functions and controlling text messaging in mines WSN	Successfully operating performance of WSN	Mohammad et al., 2017 [13]
Energy-efficient random-walk scale-free topology model (RSTM)	Cluster heads selection by using a random-walk strategy	Strong tolerance to random failures	Yourui et al., 2018 [14]
Optimization method for the monitoring in underground coal mines based (WSN)	Minimum desired lifetime according to the mining schedule in WSN	Reduces deployment costs and maximizes WSN lifetime	Alfonso et al., 2018 [15]
Energy efficiency in mines application	Finer Force Care-up (FFC) to calculate the remaining energy between the sensor nodes	Improves the lifetime of the underground sensor networks	P.Rama et al., 2019 [16]
Localization and monitoring in underground mines	Energy efficiency routing strategy based on QoS	Optimizes route existence and reduces End to End BER	Abdellah et al., 2020 [17]
Energy evaluation for WSNs multipath routing in Mines	Base stations share network information with all nodes	Enhances multipath routing mechanism	Priyadharshini et al., 2020 [18]
Smart monitoring systems for Underground Applications	Artificial neural network for data fusion and emergency classifications	Good monitoring effect and impact on underground monitoring	Lixin Wang et al., 2020 [19]
Fuzzy rules mechanism to take routing decisions	Enhance the WSN network lifetime and energy	Outperforms equalized cluster head protocol	Pandiyaraju et al., 2020 [20]
	efficiency during routing processes		
Optimal forwarding algorithm for underground WSN energy consumption	Spread sensors evenly in mine tunnels and dynamically balance energy	Longer network life cycle and optimal node energy utilization	Bin Wu et al., 2020 [21]
Clustering-based protocol anti-fail routing protocol	Minimize the number of hops in available alternative Paths	improves network lifetime and management nodes efficiency	Alharbi et al., 2021 [22]

TABLE 2. *(Continued.)* **Summary of energy efficiency studies in WSN for underground mines applications.**

Sparrow Search Algorithm for cluster head selection	Best possible CHs selection by exploiting alive nodes and dead nodes counts, throughput, and residual energy	Enhances the lifetime of nodes	Panimalar et al., 2021 [23]
Energy-efficient electrostatic discharge algorithm	shortest path routing from sensor nodes (SNs) to cluster head (CH)	Reduces the dead Nodes Count	Jagan et al., 2022 [24]
Enhanced Heterogeneous Gateway-based Multi-Host Routing (HMGEAR)	CH based on the remaining energy, multihop communication mechanism, and energy holes elimination	enhances the network stability period, throughputs, and lifetime	Jibreel et al., 2022 [25]

IV. TECHNICAL BACKGROUND

WSNs are increasingly being used to monitor underground mine environments. They enable communications between the underground sensors and the surface monitoring center. It is difficult to achieve effective underground mine monitoring by WSNs because of many challenges related to the channel environment, frequency selectivity, and sensor node power consumption.

The review of the required technical background is divided into three categories: the first summarizes the underlying methodology of WSNs for mine monitoring deployments and the topology used [12]. The second summarizes the features of clustering-based WSNs for energy efficiency and the third reviews the main heterogonous WSN models for mine applications.

A. AD-HOC WSNS TOPOLOGIES FOR MINES APPLICATIONS

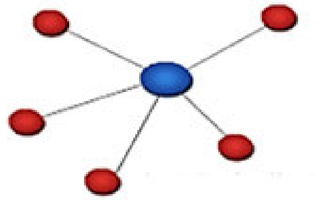
Underground miens applications must operate in difficult conditions due to the complex shapes and many mine different structures and topologies. The different forms of mines impede the process of transmitting data and monitoring through sensor networks. The mining exploration method determines the shape of the distribution of the sensors in the drilling area. Instances of mine topology and structure are room and pillar, cut and packing or the long wall method. Practically, sensor networks must be designed that can adapt to the shape of the mine environment [13].

Furthermore, they can be in operation for several months or years while ensuring the twin objectives of suitable coverage and efficient connectivity [27]. In underground mine applications, different sensor topologies are used to provide monitoring and information exchanges between the sensor nodes and surface center. These topologies are reviewed below (see Figure 3).

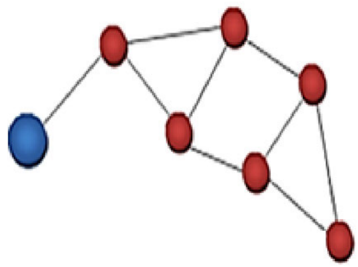
- *Single hop star topology*: This topology is considered the simplest topology for WSN configuration, where communications take place from many to one. In this topology, transmitting nodes have less traffic load than the destination sensor node. The configuration of destination nodes must have high-performance characteristics because of the heavy traffic load. The use of auto management techniques in such topology helps to avoid traffic collisions from different terminal nodes [28].
- *Tree-based topology:* This topology consists of several single-hop star topologies arranged in a hierarchical structure. The sensor nodes in the lower-level star topology send data to the medium nodes, which forward the data received from lower-level sensors to the highest-level nodes.
- *Multi-hop-based topology:* This topology creates multiple routes between the sensor nodes in a mesh structure. This provides stability to the sensor network in the case of any node or link failure. Sensors are often randomly deployed in this topology, which makes the nodes form a flexible, self-organizing, and error-handling network. The multi-hop topology is favorable for deploying for larger areas and networks to provide robustness and scalability properties [17].
- *Clustered-based topology*: This is one of the best types of topology for WSN deployment, as several nodes are distributed into several clusters, and each sensor in each cluster reports to the cluster head [29].

B. WSNS BASED ON THE CLUSTERING APPROACH

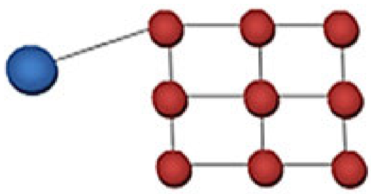
WSNs are now most commonly used in underground mining to monitor environmental parameters, including the gas amount, temperature, humidity, oxygen level, and dust. In such networks, clustering technologies aim to balance energy consumption and improve lifetime [30]. The concept



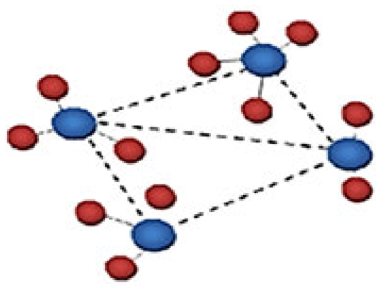
(a) Single-hop star topology



(b) Tree-based topology



(c) Multi-hop-based topology



(d) Cluster-based topology

FIGURE 3. **Wireless sensor network topologies.**

of clustering means that the sensor nodes are organized into multiple groups, called clusters in order to exchange information. Every cluster has a coordinator called the cluster head (CH), and sensor nodes within the cluster communicate to the CH as cluster members (CMs).

The CH controls the communications of member nodes by processing the environmental parameters and transmitting the data collected from these nodes to base stations. The CH sends the information it has gathered to the receiving destination by using the single hop or multiple hops mechanisms [31]. To obtain effective communication with all the sensor nodes distributed in the underground mine area, receiving stations are deployed appropriately to enable them to receive data from the network nodes and send them to the monitoring station and data center on the surface, as shown in Figure 4.

C. ENERGY MODELS FOR HETEROGENEOUS WSNS

The sensor network energy budget is related to the transmitter power and the sensitivity of the receiver. In underground applications, studies have indicated that measurements of signal energy are accompanied by an attenuation of approximately 40 db. From Table 1, the best technology that is used for such underground mines is ZigBee/802.15.4, as it has a standard wireless frequency budget of 85 dB [32].

In general, it should be verified that theoretical models of sensor nodes' energy at the transmitter and receiver in underground mine applications can create a sensor network that reduces the total energy consumption and meet the QoS requirements. For underground mine applications, two main energy models are considered for the deployment of heterogeneous WSNs: the two-level WSN energy model and the three-level WSN energy model [33].

In the two-level model, the sensor nodes are categorized by the energy level characteristics of low or high energy levels.

Assume that the low energy levels are denoted by E_1, and the high energy levels are denoted by $E_h = E_1\,(1+\alpha)$, which has more energy than E_l by α times [35]. If we have N nodes in the WSN and Nh denotes describing the number of sensors with high energy levels, where h denotes the fraction of high-level energy nodes, then $N\,(1-h)$ represents the number of sensor nodes that have low energy levels. The total network initial energy for all sensors can be expressed as follows.

$$E_{\text{total}} = N\,(1-h)\,E_1 + Nh\,(1+\alpha)\,E_1 \tag{1}$$

$$E_{\text{total}} = NE_1(1+\alpha h) \tag{2}$$

In three-level WSN energy models, WSNs consist of three categories for sensor node energy, namely, low, high, and super energy levels. By considering the same assumptions as in the two-level energy model and denoting the super energy level by $E_S = E_l\,(1+\beta)$, where β represents the factor by which the super energy level exceeds the low level [35]. Let us denote the fraction of super energy level sensors by S. The total number of high-energy sensor nodes can be denoted by $Nh\,(1-S)\,E_1$. The total initial energy for the WSN based on the three energy level models can be expressed as follows.

$$\begin{aligned} E_{\text{total}} &= N\,(1-h)\,E_1 + Nh\,(1+\alpha)\,(1-S)\,E_1 \\ &\quad + NS\,(1+\beta)\,E_1 \end{aligned} \tag{3}$$

$$E_{\text{total}} = N\,(1+h(\alpha+S\beta)) \tag{4}$$

According to the multiplicity of energy levels of the sensors used in underground mine applications, it was found that when the sensor network is deployed, depending on the sensor distribution in the application environment, the cluster head nodes consume more energy than member nodes, [36], [45].

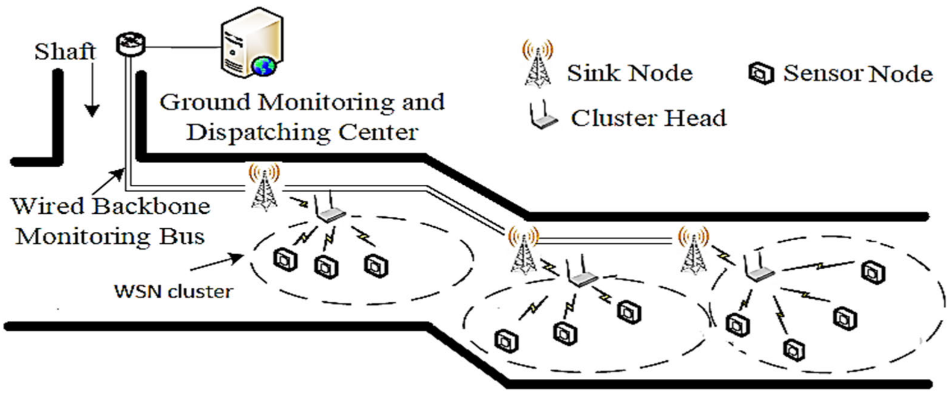


FIGURE 4. Underground WSN-based clustering approach.

The adoption of heterogeneity in energy levels for several sensors provides is more realistic than the concept of homogeneous networks because underground mine applications require different types of sensors with multiple sensitivity and energy characteristics.

V. THE METHODOLOGY

The proposed techniques for energy efficiency WSNs in underground mines are based on clustering approaches to achieve high network performance. The clustering approach will reduce the consumption of sensor energies and prolong the network lifetime. The CH selection is an important part of the WSN because CHs provide data communications between the member nodes and the base station.

Due to their heavy traffic load, CHs should have higher energy than other sensor nodes and must be able to aggregate the data. In the following, we describe the distributed energy-efficient clustering protocol (DEECP) and the proposed mechanism to enhance the process of selecting CH members. The idea is to enhance the DEECP by adding a distance-aware approach. In addition, the underground silver mine application model is described with the simulation parameters and calculation metrics.

A. THE DISTRIBUTED ENERGY EFFICIENT CLUSTERING PROTOCOL (DEECP)

The DEECP is an algorithm based on a clustering approach. The operation of cluster head selection only depends on the probability of the sensors' residual energy and average energy. The algorithm enables sensor nodes with more energy to have a high priority to become a CH [37]. DEECP is more suitable for heterogeneous WSNs. The CH selection is made according to the probability calculations of the initial and residual energy levels for all sensor nodes.

The probability of CH selection can be calculated by Equation 5, where i denotes the network time and $E(r)$ represents the average energy of the network during period r. The threshold of cluster head selection is calculated by Equation 6, which describes the nodes likely to become CHs. Figure 5 shows the flowchart of the DEECP algorithm.

$$\mathrm{P_i} = \mathrm{prop}\left(1 - \frac{E\ (r) - Ei(r)}{E(r)}\right) = \mathrm{prop}\frac{Ei(r)}{E(r)} \tag{5}$$

$$\text{Threshold} = \frac{Pi}{1 - pi(rmod\frac{1}{pi})} \tag{6}$$

The algorithm sets many nodes that are likely to become a cluster head during period r in a group. Therefore, each node is eligible to be a CH, and it chooses a random number between 0 and 1. The chosen random number is compared with the threshold and if it is less, the node becomes a CH during the current period r. According to previous evaluations, the nodes with higher residual energy take more periods to be the CH than the lower ones [38], [43].

The average energy of the nodes is calculated as a reference. It expresses the energy that must be present in each node throughout the r periods to operate the network for the maximum possible lifetime. The average energy can be calculated as follows.

$$E\ (r) = \frac{1}{N}E_{total}(1 - \frac{r}{R}) \tag{7}$$

where, N represents the number of sensor nodes, r denotes the operation period, and R denotes the network lifetime. The operation period represents the network rounds depends on the size of the network, the dimensions of each group of nodes that complete its process in the same time and the number of rounds associated with each group of nodes.

The algorithm enables all nodes to consume the same amount of energy for each operating period and to save power on the nodes' batteries. In other words, the algorithm controls energy consumption according to the amount of energy currently it has. From this, it was found that the actual energies of the nodes fluctuate according to the estimated average reference energy to ensure that most of the nodes die at the same time during a specific period.

Algorithm 1 Distributed Energy-Efficient Clustering Protocol (DEEC)

Initiate nodes
Calculates the alive nodes
Calculates CHs percentage
Calculate the residual energies of alive nodes and network average energy
for (normal and advanced nodes)
Calculates the probabilities for nodes to become CHs by Equation (5)
{
if(node not a CH in the previous round)
Node belongs to the set of the selected node to serve as CH
Elected nodes chose a random number between 0 and 1
else if (random number < predefined threshold fraction)
Node acts as a CH for the current round
}
else
Node act as a cluster member(CM)
The node sends data to the appropriate CH
end if
end for

The implementation of DEEC requires that the nodes are close to the base stations because DEEC is designed based on the assumption that the base station is located at the network center [38].

Although the probability of selecting nodes to become a CH is more accurate according to the nodes with relatively high initial and residual energy, it is possible to select the nodes with low energy, which reduces the network lifetime. Algorithm 1 shows the DEEC process.

DEEC estimates the optimum lifetime value of the network based on the calculation of the reference power of each node during each round. If the network consists of N nodes uniformly distributed within an area, the network is organized in a clustering approach. The CHs will send the measured information to the base station located at the center of the area. The calculation of two-level heterogeneous networks is done according to the energy categories of nodes.

B. ENHANCED ENERGY EFFICIENCY BASED ON CLUSTERING DISTANCE AWARE APPROACH

In general, for WSN-based IoT, the clustering approach uses a single-hop mode, which enables the close CHs to communicate with the base station. However, for underground mine applications, the single-hop mode over long distances will make sensor nodes consume much energy and many nodes will die quickly during the network cycle.

The use of the multi-hop mode helps to reduce energy consumption by dividing the long communication distance into short distances. Sensor nodes are clustered and distributed with CHs, which enables the balance of energy consumption. However, this clustering scheme may increase energy consumption in a real-time network.

In the multi-hop inter-cluster transmission scheme, cluster members (CMs) send their data directly to the CHs. Some CMs communicate directly to the base station (BS) if they are close. Due to this approach, the general energy consumption computation is based on the data packet transmitted and communication distance [44]. The energy consumption of each sensor node can be calculated as follows.

$$\mathrm{E_{Tx}} = k(E_{elec} + E_{amp} * d^2) \tag{8}$$

where, E_{elec} and E_{amp} represent the electronic circuit and amplified transmitted signal energies, respectively. k is the data packets in a bit, and d is the communication distance.

The calculation of *CM* energy consumption depends on the initial energy of the sensor node, which is given by Equation 9, and the power consumed by the CH is given by Equation 10.

$$\mathrm{E_{CM}} = E_{init} + E_{Tx}(k, d) \tag{9}$$

$$\mathrm{E_{CH}} = E_{init} + E_{std} \tag{10}$$

where, E_{init} *and* E_{std} represent the initial energy of the sensor node and the standard energy consumption of a node taking part in the CH selection phase, respectively. E_{std} depends on the transmitted energy and the energy consumption of the node for the data aggregation process.

The proposed mechanism calculates the probability of different sensor energy levels to select the CHs based on DEECP. In addition, it uses the three-level WSN energy model. In addition, the probability set also depends on the average communication distance between the node eligible to become CH and the base station. A long-distance gives a low probability of becoming a CH, and a short distance gives a high probability [40]. Figure 5 shows the flowchart of the proposed algorithm. The probability calculations for all energy levels depend on the initial energy. The probabilities of CH selection is defined by Equation 11. The threshold of

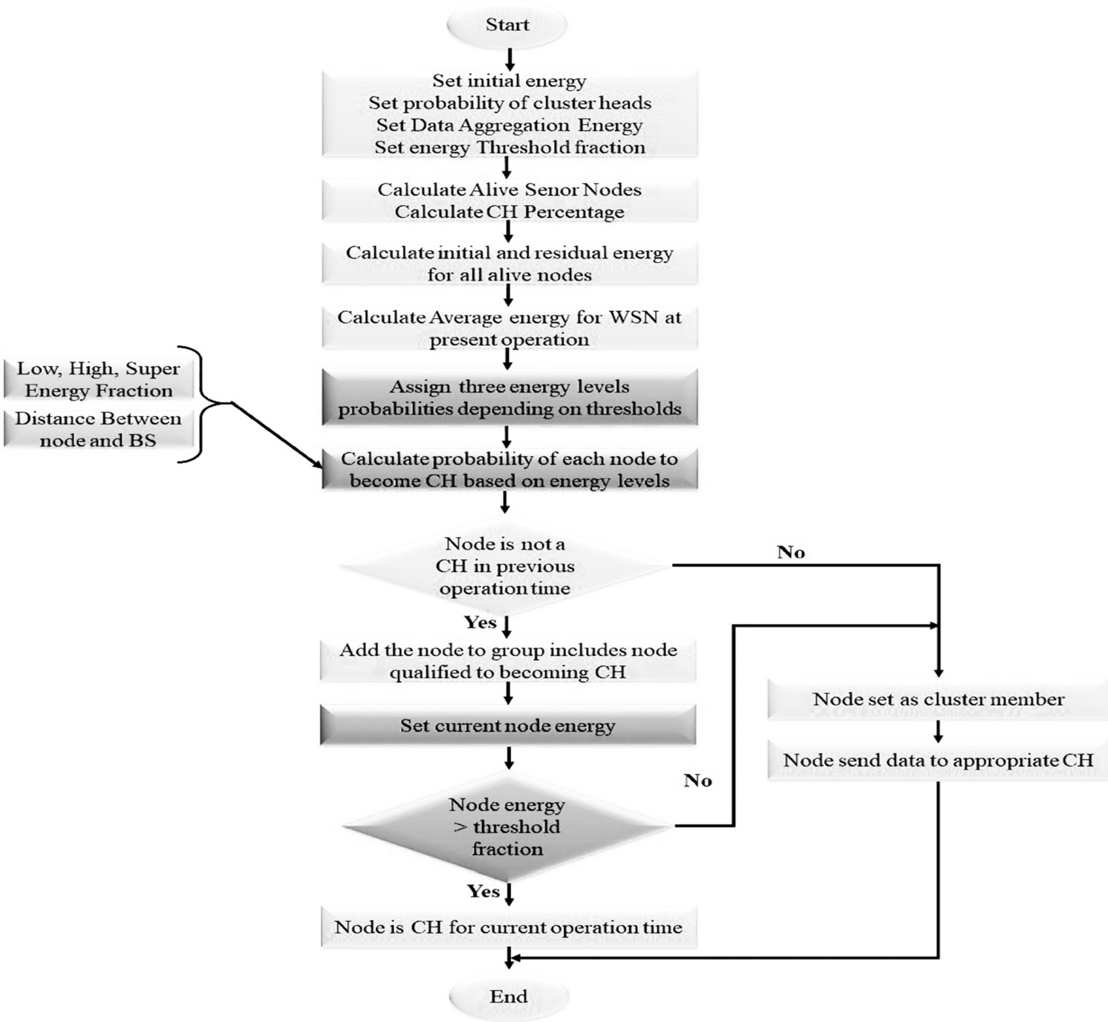


FIGURE 5. Enhanced energy efficiency based on a clustering distance-aware approach.

cluster head selection is calculated by Equation 12.

$$\mathrm{Pi} = \left(\frac{prop\ Ei(r)}{(1 + h\,(\alpha + S\beta)\,E(r))}\right),\quad for\ all\ \text{energy}\ probabilities \begin{cases} \text{low level} \\ \text{high level} \\ \text{super level} \end{cases} \tag{11}$$

$$\text{Threshold} = \frac{Pi}{d(1 - pi(rmod\frac{1}{pi}))},\quad for\ status \begin{cases} \text{d} \gg \text{low probability} \\ \text{d} \ll \text{high probability} \end{cases} \tag{12}$$

The calculation of the average distance (d) between nodes eligible to become CH according to the power level estimates helps to estimate the power consumption so that the power required to transmit the data is determined according to the average distance between the node and the station [41], [44].

By assuming that the base station is located at coordinate (0, H) and that the eligible node as a cluster head is at coordinate (x, y), the estimated average residual energy based on the average distance between the candidate's node and the base station can be calculated by Equation (13). The distribution function of a cluster head node is denoted by ρ(x, y).

$$\mathrm{E}[d^2] = \rho \iint x^2 + y^2 - 2\mathrm{yH} + H^2\,\mathrm{dxdy} \tag{13}$$

In this algorithm, each node works independently and presents itself as having been elected to be the temporary CH of the members' group according to the probability threshold calculations by Equation 12. It is assumed that the distance between the selected node and the station is determined according to the RSS.

C. UNDERGROUND SILVER MINE MODEL

The distribution of the sensor nodes in the underground mines depends on the mine topology and structure. Several methods are used for production in mines, such as room and

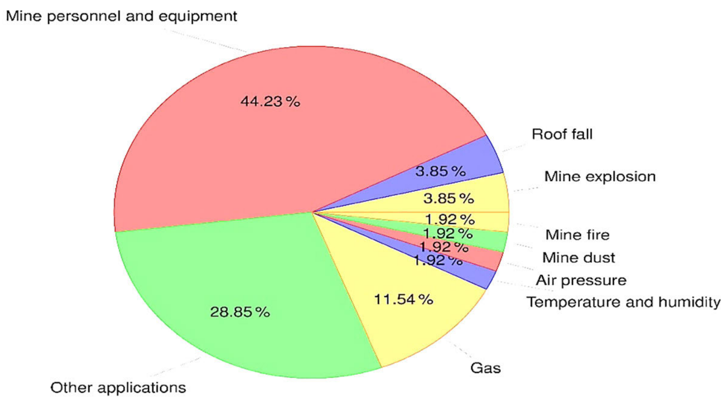


FIGURE 6. Underground mining environment monitoring issues.

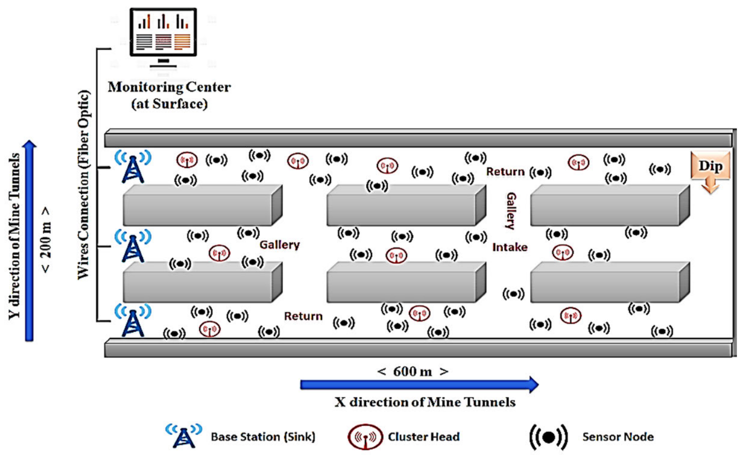


FIGURE 7. WSN deployment model for silver mine applications.

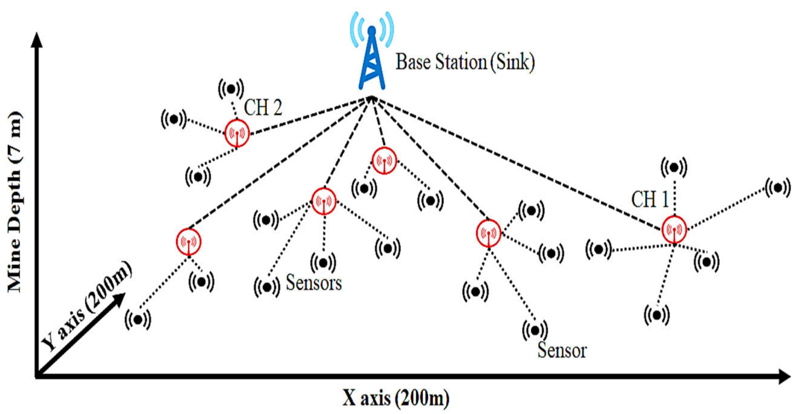


FIGURE 8. WSN based on clustering communications for simulation scenario.

pillar, as shown in Figure 8. In the room and pillars method, the pillars are used for load balancing on the mine during mining, whereas the rooms are located between the pillars for production. As shown in Figure 8, the mine areas are divided into sections, and each can communicate with the base stations [41], [47].

The WSN can form one or more CHs with a large number of nodes in each mine section. The sensor nodes distributed in each mine section enable sensing of the state of various hazardous variables, such as temperature, humidity, air concentration, and vibration (see Figure 6). In addition, the sensor nodes transmit the sensed data to the CHs, where the

CHs in turn sends the received data to the base station (see Figure 8). Every CH must be connected to the base stations according to the CH selected in a reliable and fast way. The base stations are assumed positioned in the center of the mines and connected to the monitoring surface center via wired communication methods such as Can Bus or optical fiber.

In our work, the sensors are assumed to be deployed randomly in the underground mine environment with a 200× 200 area size and mine depth approx. to 7 meters, as shown in Figure 7. This assumption is practical since one cannot use deterministic sensor deployment for sensing large areas. The sensors are assumed to communicate with the fixed base station through the selected CHs and are assumed to always have data to transmit. In addition, in our model, the base stations are located at the center of the selected region.

Because of heterogeneity in sensor node energies, the initial energy of nodes is randomly distributed between E_l and $(1+\alpha\ \max)\ E_l$ for all sensor nodes [42]. where, E_l represents the minimum energy and αmax denotes the heterogeneity factor as a max percentage of additional battery power [46].

In our mine WSN, sensor nodes have initial energy equal to $(1+\alpha)\ E_l$ where α represents the increase in energy in terms of the initial level E_l. In the WSN, we assume that the sensor nodes receive information about the network energy by messages broadcast from the base station. In the proposed study, the nodes are distributed randomly in a specified mine area, the CHs collect data from the sensors while neglecting the data redundancy, and the data have a fixed length package because of high correlation.

D. EVALUATION PARAMETERS AND METRICS

We simulated the wireless sensor network in a MATLAB® environment in a 200m X 200m underground mine area. Table 3 shows the simulation parameters used. We consider a WSN with 50, 100, and 150 nodes, which are randomly scattered in a square area of 200 m. The base station is set in the center of the mine area.

The communication ranges of clustering and member sensors are short ranges communication, within 2 to 4 meters for the miner's localization, and 6 to 11 meters for roof falls. The total traffic load is between 200 to 1000 packets according to the sensor nodes' operations. The sensors used in experiments with 200 to 600 messages, were simulated under the condition of low-power wireless technologies using IEEE Zigbee/802.15.4 standard.

The performance metrics are used to evaluate the distributed energy-efficient clustering protocol, and they are network lifetime, nodes alive during simulation time, and network throughput [35]. The lifetime describes the all-node power consumption duration, which shows the network lifetime before the sensors' energies are fully consumed [36].

The number of live sensor nodes is evaluated by extracting the number of nodes still alive during the simulation time. The network throughput can be described by the amount of the packet transmitted to the base station. The evaluation will show the performance of the WSN in terms of the network stability period, power consumption, and data sent to/received by the base station, in addition to the lifetime of WSN networks [37], [38].

TABLE 3. WSN paramagnets for underground WSNs.

Network Parameters	Values
WSN area size	200 × 200 m
Mine depth	7 m
Number of nodes	50,100,150,200
Initial energy	0.5J
Packet size	3000 bits
Max data rates	250kbps
Modulation standard	Zigbee/802.15.4
Data aggregation (compression energy)	5nJ/bit/signal
Transmit/Receive energy	50 nJ/bit
Free space loss	10nJ/bit
Multipath loss	0.0013pJ/bit
Simulation time	10000 sec

VI. RESULTS AND DISCUSSION

The results of the performance evaluation of DEECPs and the proposed mechanism will be discussed in this section. Through the analysis, we show that the longest network stability period, when power consumption has stabilized and there is an energy balance in the network, is a target of the protocols whose performance has been measured. We consider that all nodes are fixed or in micro-mobility. We also ignore the energy loss due to dynamic random channel conditions and fading effects.

A. GENERAL CASE

We evaluate the proposed mechanism with 50 sensor nodes. The fractions of high and super energy levels are given by $h = 0.5$ fractions of high energy and $S = 0.4$ fraction of super energy with the energy increased by $\alpha = 1.5$ and $\beta = 3$ times more than low energy, respectively. Figures 9, 10, and 11 show the results of the evaluated energy-efficient base clustering mechanisms as follows.

From Figures 9, 10, and 11, we observed that the proposed mechanisms make the WSN more stable than using the DEECP. From Figure 9, we conclude that the machine achieves a long lifetime to the WSN because the sensor nodes with high and super energy levels die more slowly than sensors with low energy levels.

Figure 9 shows that the first node dies in the duration time 885 when using the DEECP, while by the proposed algorithm, nodes live until duration time 400, and the first node dies at 436. This is because of variations in the nodes' energy levels,

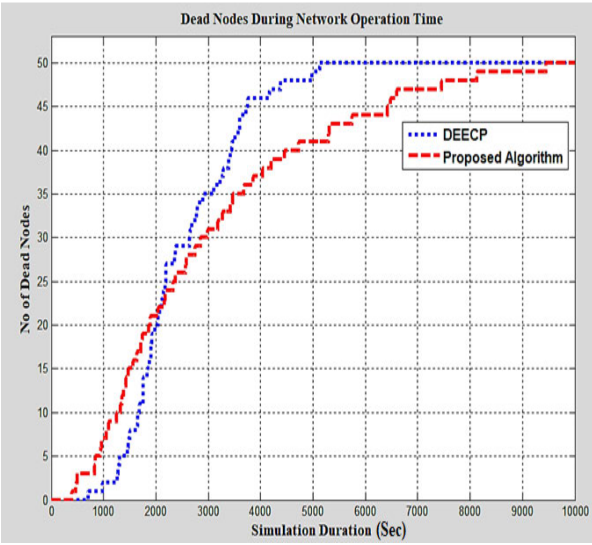


FIGURE 9. Number of dead nodes during network operation for DEECPs versus proposed algorithm comparison.

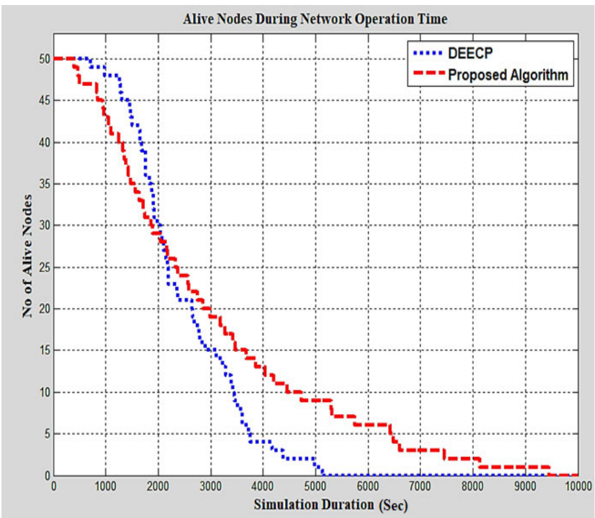


FIGURE 10. Number of alive nodes during network operation for DEECP vs. Proposed algorithm comparison.

but in a few fractions of durations, the proposed algorithm keeps nodes alive longer than the DEECP. Due to the fusion between the proposed mechanism and cluster head election based on DEECPs and considerations of sensors' energy levels, the mechanism takes some advantage of DEECPs in terms of the first node dying and prolongs the stability time.

As shown in Figure 10, the proposed mechanism keeps more nodes alive for a long network operation time than the DEECP. As shown in Figure 10, the stability region of our proposed method is 436 ms, which is large compared to DEECP with 885 ms. All nodes will die in 5580 durations when using DEECP, whereas the proposed algorithm keeps all nodes alive until 9938 duration time. We notice that the mechanism shows a significant improvement of 24% over DEECPs in terms of the last node alive.

After the stability region, our proposed algorithm the active nodes die much slower than in the DEECP protocol. The

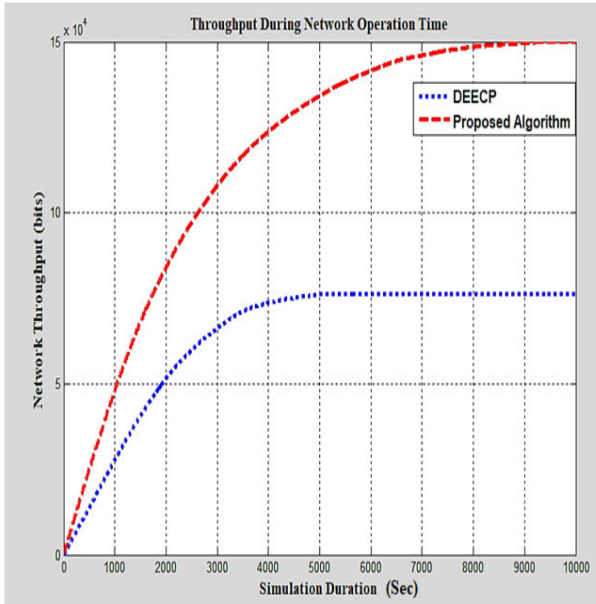


FIGURE 11. WSN network throughput comparison for DEECP and proposed algorithm.

cause of active nodes remaining alive for a longer time is because the proposed algorithm keeps a better energy consumption distribution, which leads to the nodes consuming energy equally during the same period.

This performance results from modifications in the DEECP by considering the heterogeneity of node energies to calculate the probability of optimal cluster head selections. In addition, there is a close distance dependence between nodes and the base station. The mechanism can also enhance the WSN network throughput due to its ability to reduce energy consumption and increase the WSN lifetime, as observed in Figure 11. This figure presents the network performance (bps) by simulation duration. The network performance for both protocols has a rising trend at the beginning. The DEECP continues to be stable after 4000 durations while the proposed method after 9000 durations. However, the maximum performance for DEECP was 75 kbps, while the proposed algorithm outperformed the legacy DEECP by achieving 150 kbps. These results establish the efficiency of the proposed algorithm and the significance of our modeling that leads to selecting high-powered nodes as CHs.

According to the results obtained, sensor nodes remain more active by the proposed approach if they are connected to the CH and have enough energy to communicate with the CH. Moreover, the approach also enables a selection of CHs with enough energy to be active to transmit the aggregated data to the base station.

B. IMPACT OF NODES NUMBERS

Both the DEECP and proposed algorithm were analyzed based on the effect of the number of sensor nodes used in the WSN.

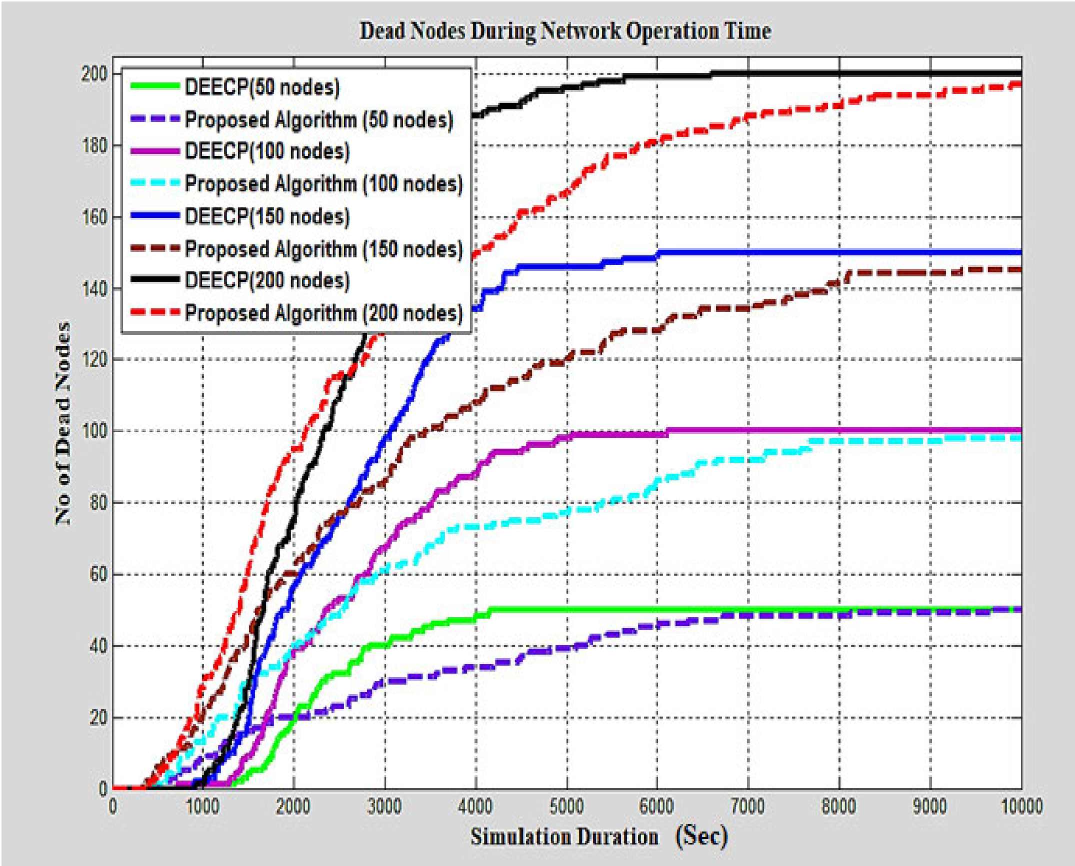


FIGURE 12. Number of nodes impacts the performance of the studied algorithms in terms of the dead nodes.

From Figures 12 and 13, it is noticed that when increasing the number of nodes in a stable operating period, algorithms exhibit high performance and the proposed algorithm provides higher performance. It is also evident that the percentage of nodes selected to be optimal CHs will have increased, especially for the proposed algorithm.

When the number of nodes increases, there is an improvement in the performance of the network, which reflects an impression that the energy consumption is distributed fairly on the network and increases its stability period. The same parameters shown in Table 3 were adopted, with the change in the number of nodes to be 50, 100, 150, and 200 to evaluate the impact on the network stability.

In general, the proposed algorithm gives the best performance because of its ability to choose the best nodes with stable and high energies to become a CH in addition to those that are closer to the base station. From Figure 14, we observe that the increase in the number of nodes allows the proposed algorithm to keep the nodes alive as much as possible during network operation, in which nodes with higher energies are enabled to support the network as a CH for a long period. Hence, in the case of a simulation duration of more than 10000 rounds, the proposed algorithms ensure a long lifetime for WSN operation.

However, an increase in the number of nodes will improve network performance and ensure a long operating period by the proposed algorithm. An increase in the number of nodes may be considered as increasing the cost of WSN deployment and requiring the spreading of many sensors in the underground mine environment. However, the performance of the proposed algorithm and its effect on the network is related to the duration period of WSN operation. Hence, a balance can be made between the required network operating periods with the number of nodes used in the network to obtain a high performance that meets an acceptable level of deploying costs in the underground exploration environment.

Moreover, the proposed algorithm with a higher number of sensor nodes enables the collection of more data from the underground environment mine area and keeps reducing the pressure of the total data on the network. When the volume of data that is dealt with on the network increases, the percentage of energy consumption may increase in selected CHs. However, the algorithm preserves the stability of the network for the longest possible period by the possibility of choosing the most favorable nodes.

VII. CONCLUSION

In this paper, we have proposed an enhanced DEECP protocol for heterogeneous underground mine WSN applications.

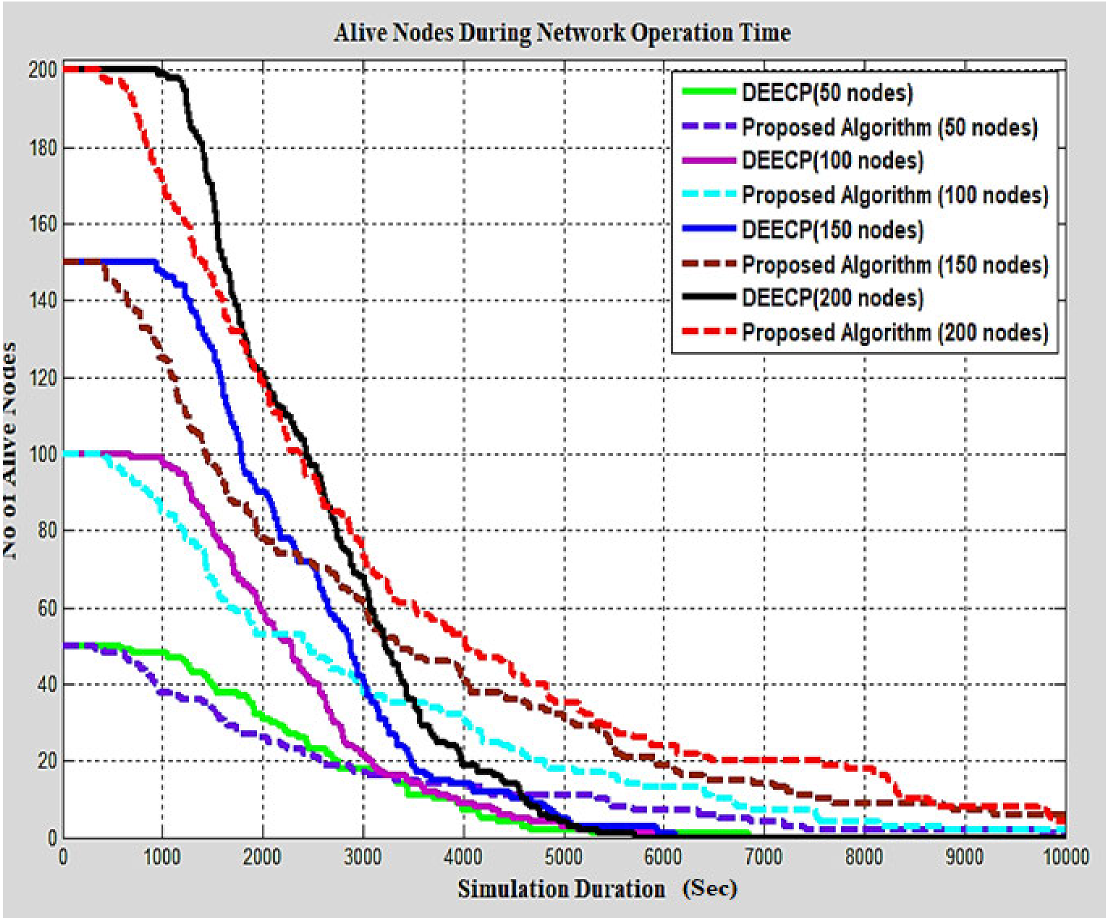


FIGURE 13. Number of nodes impact the performance of studied algorithms in terms of alive nodes.

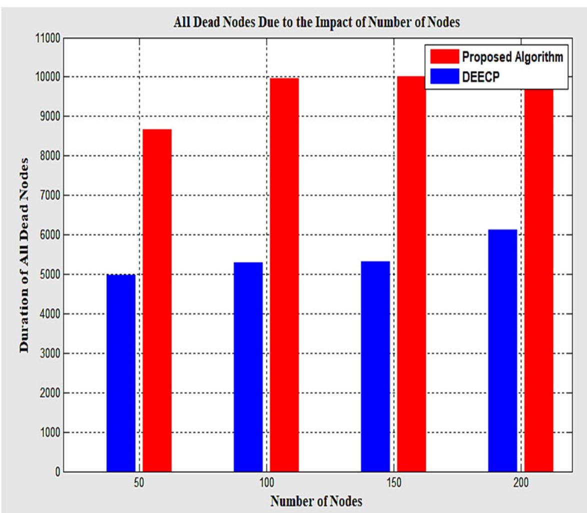


FIGURE 14. Number of nodes impacting the network lifetime based on studied algorithms.

From the literature, the DEECP is an energy-aware clustering approach for WSNs. It enables two energy levels depending on the residual and average energy calculations. However, in heterogeneous WSNs, it cannot provide efficient performance due to variations in sensor energies. Our proposed mechanism enables us to deal with three types of energy levels and perform a distance-aware CH selection. We analyzed the performance of the proposed algorithm in comparison with DEECPs in terms of the number of dead sensors, the number of live sensors, and network throughput. The evaluation results show that the proposed algorithm outperforms DEECP.

The improvements to DEECPs have enhanced the election of cluster heads and increased the network lifetime by a factor of 24%. Through the presented study, it is found that it is difficult to extend the life of the nodes and be able to stabilize the WSN for a relatively very long period due to the limits of the node's energies. Although the use of the proposed algorithm added a measure of stability in network performance, the network deployment process in an underground environment remains a topic that needs further study.

Our next study will aim to improve the current algorithm to optimize the selection of the cluster head by using AI techniques such as Q-learning and swarm intelligent optimization. The goal will be to identify many parameters related to the proximity of the nodes to each other and their closeness to the station, as well as the accuracy of the CH selection. In addition, flow calculations for determining the volume of information that is exchanged by CH according to the type of sensors used will also be explored.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

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