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Optimization and Analysis of Wireless Networks Lifetime using Soft Computing for Industrial Applications

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Recently, wireless networks are applied in various engineering and industrial applications. One of the critical problems in wireless network system optimization in intelligent applications is obtaining an adequate energy fairness level. This issue can be resolved by applying effective cluster-based routing optimization with multi-hop routing. Hence a new network structure is developed that is derived from energy consumption architecture by applying soft computing strategies such as evolutionary operators in determining the exact clusters for optimizing energy consumption. The new effective evolutionary operators are tested in the optimization of a lifetime. The proposed method is simulated for different values of the routing factor, α, for different types of networks. The energy levels range from 0.4 to 0.8, achieving good results for nearly 2500 rounds. The proposed strategy optimizes the clusters, and its head is selected reliably. The optimization of cluster head choice has been done based on the base station distance, the energy of the node, and the node's energy efficiency. The reliability of the long-distance nodes is increased during the data transmission by modifying the size of the area of the candidate set of nodes in contrast the near-distance node's energy consumption is reduced. For the energy levels that range from 0.4 to 0.8, the higher network throughput is obtained at the same time network lifetime is optimized compared to other well-known approaches. The proposed model is expected for different industrial wireless network applications to optimize the systems during the long-run simulation and to achieve high reliability and sustainability.

Keywords: Clustering, Energy consumption, Evolutionary modeling, Network optimization, Throughput

Introduction

There are many application domains in which wireless-based sensor networks are implemented with several base stations and nodes. The network architecture affects performance in several ways. Since there are many nodes in the wireless networks, it is necessary to devise a mechanism to minimize the energy consumption. Different protocols are also required for cluster-based separation operations, and the hierarchical approaches applied.[1] A suitable routing protocol should be designed for energy-constrained wireless networks with effective data transmission. Hence it is essential to avoid congestion of channels, enhancing utilization such that the network's traffic is balanced. The routing protocol should also be designed to ensure in such a way that the energy of the node should be efficiently used.

This research develops a new evolutionary model with an effective cluster-based routing mechanism for industrial applications to optimize network system performance. Hence a new network structure is developed concerning energy consumption architecture by applying evolutionary operators in determining the clusters for optimizing total energy consumption. The new effective evolutionary operators are tested in the optimization of a lifetime. The novelty of the proposed model is as follows:

- Construction of new network architecture using energy consumption and evolutionary development model to determine the clusters and optimize energy consumption.
- Load reduction using evolutionary operators and finding a good range of routing factors, α for all network instances.

Survey of Literatures and Analysis

The protocol and cluster-based architectures such as LEACH, HEED, SEP, and DEEC are developed. The stochastic and chained cluster strategies are applied with some protocols. Some architectures are applied to the soft computing paradigms to obtain the exact cluster count.[2,3]

Hierarchical and hybrid clustering minimize the hops by applying different cluster-based operations.[4,5]

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The various neural network-based learning methods and algorithms are designed to increase the performance in wireless sensor networks. The methods such as ant colony optimization, swarm intelligence, and hierarchical and heuristic protocols are also developed for route identification from source to destination.[6] Some of the recent techniques developed for lifetime optimization are energy hole strategy, cyclic opportunistic routing, device relaying scheme, collaborative data scheme, dynamic duty cycling, cooperative cache strategy, cluster formulation, multi-path load balancing, heuristics with clustering, task allocation, multiple virtual scheduling, extended routing, scalable routing, dynamic diffusion, and topological learning protocol schemes. The analysis of the survey of kinds of literature results in the following critiques:[7–10]

- Lifetime optimization is predicted within the expected range
- Not analyzed the exact cluster count
- Energy balancing has not been done through an optimized approach
- No generic strategies for common networks

The devised architecture resolves these issues by applying the new approaches[8–12]

- Construction of new network architecture based on original energy consumption
- Design of a new evolutionary approach to obtain the exact clusters required
- Design of a new evolutionary approach to optimize energy consumption
- Finding a good range of routing factors, α for all network instance
- Evaluation of evolutionary operators for reducing the load

This research develops a new evolutionary computing-based model with an effective cluster-based routing mechanism. Hence a new network structure is developed that is derived from energy consumption architecture by applying evolutionary operators in determining the exact clusters for optimizing entire energy consumption. The new effective evolutionary operators are tested in the optimization of a lifetime.

Proposed Model

To optimize the network lifetime, the traffic of data should be routed in such a way that the consumption of energy should be balanced between the nodes in the wireless networks based on the present energy proportion.[3–5] The following definitions are applied in the new optimization model that employs the different genetic operators. The architecture makes the following assumptions:

- The wireless nodes are distributed randomly within the region of monitoring.
- The node's locations with the base station are fixed.
- The sender node's transmit power is required to determine the distance to the receiver node.
- All the sensor nodes are of the same type.

Notations

The energy consumption for b information bits with a distance, d, and distance threshold d_0 is:

$$E_T(b,d) = b\,(E_{elec} + \varepsilon_{fs}\, d^2)\ when\ d < d_0 \quad \ldots (1)$$

$$E_T(b,d) = b\,(E_{elec} + \varepsilon_{mp}\, d^4)\ when\ d \geq d_0 \quad \ldots (2)$$

The receiving energy for the information of b bits is:

$$E_R(b) = E_{elec} \times b \quad \ldots (3)$$

The value of d_0 is:

$$d_0 = \sqrt{\varepsilon_{fs}/\varepsilon_{mp}} \quad \ldots (4)$$

The consumption of energy to transmit the information of b bits with $d_{ch} = distance$ (ch, cluster node) is:

$$E_{non-cluster} = E_R(b) + b\,\varepsilon_{fs}\, d_{ch}{}^2 \quad \ldots (5)$$

The node's total consumption of energy is:

$$E_{cluster} = (n/k\text{-}1)$$
$$E_R(b) + n/k\, b\, E_{DA} + E_R(b) + b\,\varepsilon_{fs}\, d_{ch}{}^2\ if\ d_{ch} < d_0 \quad \ldots (6)$$

$$E_{cluster} = (n/k\text{-}1)$$
$$E_R(b) + n/k\, b\, E_{DA} + E_R(b) + b\,\varepsilon_{mp}\, d_{ch}{}^2\ if\ d_{ch} \geq d_0 \quad \ldots (7)$$

The exact cluster k_1 for the diameter dr and radius r is:

$$k_1 = dr^2/8r^2 \quad \ldots (8)$$

The exact clusters count is:

$$k = \sqrt{dr^2 n \varepsilon_{fs}/8A} \quad \ldots (9)$$

The weighting model for cluster optimization is:

$$f(i,j) = \frac{\omega E_i}{d(i,CH_j)} + (1-\omega)\frac{CH_j}{d(CH_j,BS)} \quad \ldots (10)$$

Proposed Architecture

The proposed architecture to design the intelligent optimization model based on the genetic operators to optimize the lifetime is discussed in this section. If any two sensor nodes are available within the communication range, then there should be an edge connecting these nodes. The target is the determination of energy effective path such that the consumption of the energy should be balanced and the network's lifetime should be prolonged. The assumption is that the isomorphic nodes and symmetric edges are considered for developing the model. The power level of the transmitter can also be adjusted to use the required energy to reach the suitable hop receiver.

The algorithm of the proposed model is depicted in algorithm 1. As the cluster, size increases then the cluster's traffic also increases. Likewise, the reduction in clusters also reduces the traffic within the clusters. Thus, the increase in traffic affects the network's increased energy consumption. Thus, it is necessary to obtain the mean clusters. The proposed model region is to be monitored as a circular region with radius $d/2$. The model constructs the square of the inline region with side l of uniform distribution of clusters. The exact cluster count is obtained for each cluster.

Algorithm 1: Optimization of Wireless Networks Lifetime

1. Define the initial values of WSN
2. Evaluate the exact clusters and update the cost of energy using greedy strategies.
   2.1 Fix the n nodes of a WSN circularly with radius d/2.
   2.2 Develop the inline square inside the circle with side L.
   2.3 Determine the required clusters
3. Use the evolutionary model to optimize the energy to clusters
   3.1 Determine the average clusters by applying a cluster-finding algorithm
   3.2 Optimize the balance energy and generate the expected clusters
   3.3 Evaluate the energy level balance heuristics and selection within the region of c_h
   3.4 Perform data transmission and fine-tune the measures of energy
   3.5 Decide the node's death and transfer the control to choose c_h in each cluster
4. Apply the heuristic search to build the clustering factor
   4.1 Decide the objects count and construct cluster partitions
   4.2 Find the minimum, and maximum distance between clusters and calculate the clustering factor
   4.3 Obtain the fixed clusters
5. Choose the cluster heads using the evolutionary model
   5.1 Fix the clusters center point
   5.2 Define the objective function of cluster nodes
   5.3 Choose two clusters nodes using crossover and mutation operators
   5.4 Obtain the better value of c_h for fixed generations
6. Reduce the load using evolutionary operators
   6.1 Calculate the dormancy factor within a cluster
   6.2 Calculate the clusters dormancy ratio and obtain its factor set
   6.3 Apply evolutionary model to load reduction of dormant vertices.

To optimize the energy consumption, the exact cluster size is required. The devised model performs the energy consumption balance by applying a node's dormancy and energy partition. The assignment of time slots of the considered cluster scheme is sketched in Fig. 1.

The average distance and the cluster variance are required to build the setup of a cluster. The model has been constructed to set up the clustering factor based on a node's continuous uniform distribution of energy consumption.The choice of selection of a $c_h$is performed for all clusters with the following constraints:

- The position of the node is nearer to the center of a cluster.
- There should be a minimum distance tothe base station.
- The residual energy of a node should have enough threshold.

The reduction of a load is implemented using the strategies[5–8] such as the selection based on the location and the distance values of c_h. For an unstable network, the data transmission distance is large and the nodes are present in large size clusters with less energy. Thus the factors such as residual energy and distance values of c_h affect the reducing the load. To achieve effective data transmission, the multi-hop method is followed for all the heads of the cluster

Initial Stage consists of size of exact cluster, setting up a cluster, choosing the heads of clusters	Slot for 1st c_h1	Slot for 1st member node's c_h1	…	Slot for nth member node's c_h1	Slot for 2nd c_h1	…

Fig. 1 — Time Slots Assignment in the proposed model

nodes. The energy consumption of the nodes for the transmission of l – bits is obtained. Compared with all the cluster nodes, the cluster head node should have more transmission work and data processing with a faster energy consumption rate. The cluster heads are selected periodically. When selecting a cluster head, other nodes follow various strategies in choosing the suitable cluster head by dividing the network into fixed clusters. When the cluster size increases, the cluster heads data burden increases, and the energy consumption rate also increases. Hence the cluster size should be reasonably controlled and the cluster head's energy consumption should be balanced. To make suitable energy constraints and balance the energy, the single-hop cluster routing scheme is applied for smaller wireless networks.

Results and Discussion

The devised method is implemented on the different heterogeneous and homogeneous networks, including NS-2.35 and some of the random networks with a varying number of vertices. The wireless network structure is built by assuming that the sensor nodes lie in the circular region with a radius d/2, where the base station is at the circle center with a coordinate (0, 0). Compared with some well-known methods, the energy consumption is optimized for the varying rounds in multiples of 100. The evaluation metrics energy consumption, control overhead, throughput, energy efficiency, energy standard deviation, route setup time, and lifetime measure are considered to evaluate the performance of the proposed model. The proposed method calculates the count of live nodes in different rounds, a round number of initial node's death, the network's lifetime, energy consumption, and throughput measures. The analysis concludes that better performance measures are obtained during the simulation over the long-run period. The simulation parameters are defined as follows: Types of networks: heterogeneous and homogeneous; range of α: [0, 1]; number of rounds: [1, 3000]; nodes: [1, 250]; initial energy: [0.2, 0.5]; diameter of region: 250m; initial nodes: 100; message size: 3000 – 4000 bits.

Evaluation of α

The simulation is conducted for different values of the routing factor α in the range [0.01, 1.0] to measure the lifetime. The initial value of energy level has been set as 0.02 in the various heterogeneous and homogeneous instances. It has been evaluated that the energy level is uniformly distributed in the interval [0.5, 0.9] to the instances of the homogeneous networks.

Analysis of Lifetime in Homogeneous Instances

The simulation has been conducted for various homogeneous and random networks with α ranging from 0.1 to 0.9 and the measures of a lifetime are analyzed. The outcomes of the simulation are sketched for different values of α from 0.1 to 0.9 and 0.2 to 0.8 are sketched in Figs 2(a) and 2(b), respectively. The maximum lifetime is attained when α = 0.1 compared to other values. It has also been reported that the initial node death occurs when α becomes negligible for the different homogeneous sensor networks. There are no significant differences that occurred when α ranged from 0.25 to 0.98. Hence a better measure of α is reached for α in [0.25, 0.59] and [0.25, 0.55] for homogeneous and heterogeneous networks, respectively.

Death Analysis for Initial Node

The wireless sensor network reaches a declining state when the starting node reaches the state – *dead*. The clustering protocol obtains the energy balance consumption over some time to choosing the cluster heads by considering the criterion – live location of the node, cluster head selection strategy. The proposed model is simulated for different instances, and the initial nodes' death has been compared with other well-known methods and presented in Fig. 3. The simulation results conclude

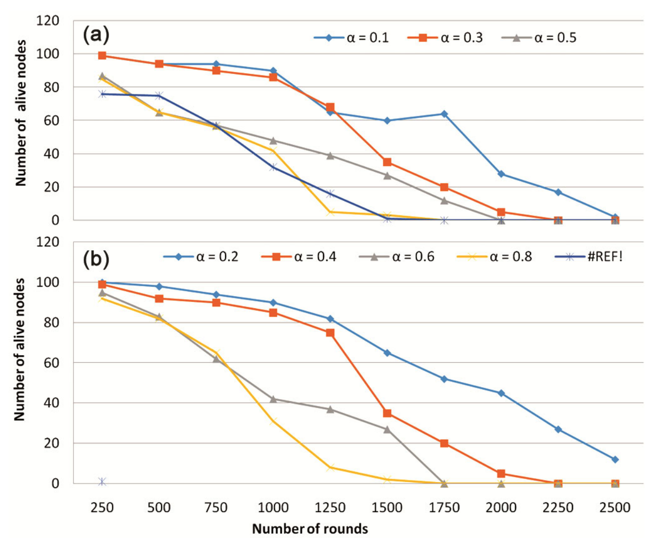

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Fig. 2 — Lifetime Measures for different values of α: (a) from 0.1 to 0.9, (b) from 0.2 to 0.8

that the devised method puts a significant delay on the starting node compared to other strategies. The significant delay is achieved based on the analysis of nodes' live location and the energy level of the cluster heads.

Lifetime Analysis

For the varying energy levels considered, the wireless networks' lifetime is calculated and depicted in Figs 4 to 6. For the considered different energy levels, the proposed research increased the lifetime percentage significantly compared to other methods. Thirty-nine nodes survived at the 1400th round with 0.4 energy, but other strategies SEP and LEACH lost their life before the 1400thround. The proposed method is also in the live state during the 1500th round. Likewise, with 0.8 energy, SEP and LEECH lost a lifetime before 2500 rounds. At different iterations the live nodes count are (3000 – 5, 2800 – 13, 2600 – 22, 2400 – 39, 2200 – 62, 2000 – 87) respectively. From the experimental results, when the energy lies in (0.3, 0.9), the proposed research obtained a better and more significant percentage of performance measures for the higher rounds compared to other strategies.

Analysis of Energy Consumption

This research obtains the expected clusters count to the network structure. The suitable cluster head is determined based on the node location and energy. The cluster head is chosen reliably, and the reasonable count of clusters is fixed in this research compared to the other approaches. The simulation results conclude that the energy consumption is much reduced over the other approaches and are sketched in Figs 7 to 9.

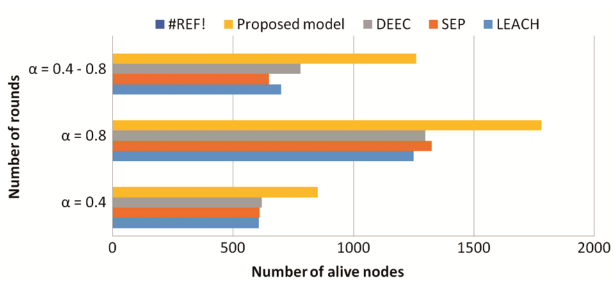

Fig. 3 — Comparative analysis of initial nodes death

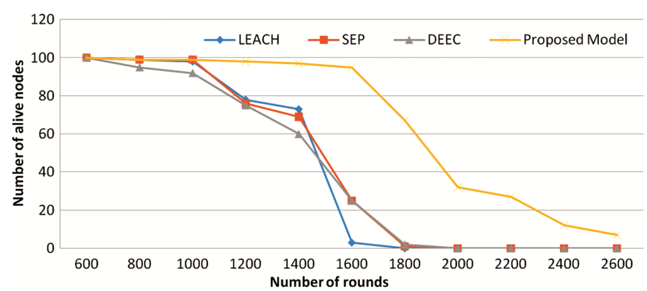

Fig. 6 — Energy lifetime analysis (0.3, 0.9)

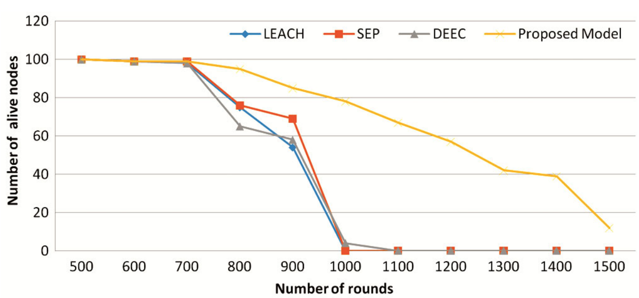

Fig. 4 — Lifetime analysis (Energy: 0.4)

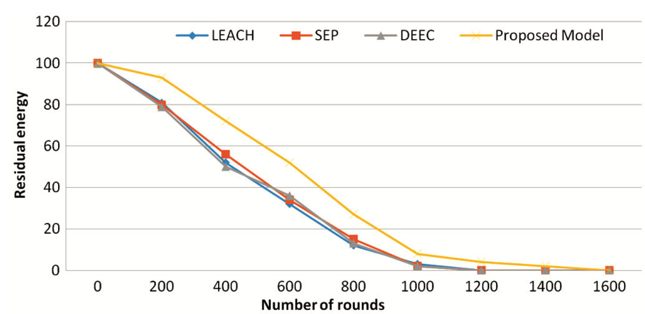

Fig. 7 — Round vs. Residual Energy with energy: 0.4

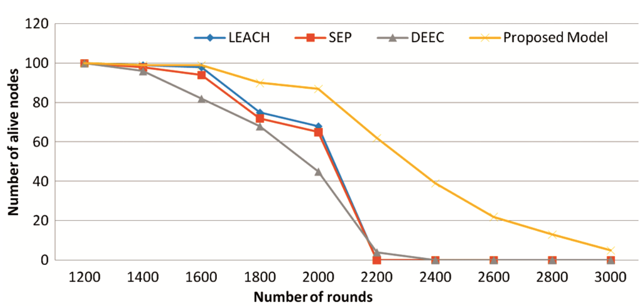

Fig. 5 — Lifetime analysis (Energy: 0.8)

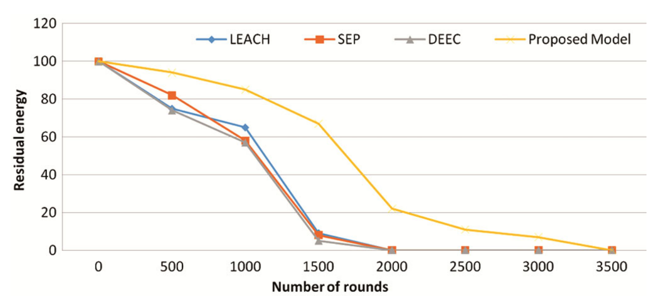

Fig. 8 — Round vs. Residual energy with energy: 0.8

Table 1 — Performance Analysis with other schemes (energy – {0.4, 0.8, (0.4, 0.8)}

Protocol	Stable Time	Unstable Time	Network Lifetime	Final Throughput
LEACH	(654, 1320, 746)	(275, 499, 865)	(929, 1819, 1611)	(5404, 10099, 8017)
SEP	(663, 1345, 674)	(252, 470, 1018)	(915, 1815, 1692)	(5357, 10336, 10591)
DEEC	(680, 1326, 813)	(332, 718, 1058)	(1012, 2044, 1871)	(7072, 13590, 12426)
Proposed Method	(789, 2588, 1267)	(592, 1032, 890)	(1418, 2595, 2017)	(12382, 20512, 17412)

Table 2 — Performance measures – (static, dynamic) for the static, dynamic networks with 100 vertices[8–12]

Metric	EBAR-P	EBAR-R	EEABR	Sensor Ant	IACO	Proposed Method
Energy	(146.4, 111.4)	(158.2, 139.4)	(235.2, 152.6)	(249.7, 174.6)	(188.2, 121.4)	(145.2, 110.2)
Throughput	(1.68, 0.7)	(1.47, 0.51)	(0.77, 0.6)	(1.09, 0.24)	(0.79, 0.62)	(1.72, 0.72)
Overhead	(0.36, 0.47)	(0.36, 0.5)	(0.47, 0.2)	(0.47, 0.56)	(0.44, 0.51)	(0.35, 0.45)
Efficiency	(5.86, 3.96)	(3.87, 2.61)	(1.97, 0.66)	(2.68, 0.76)	(4.69, 2.93)	(5.92, 3.98)
Deviation	(4.03, 2.36)	(2.90, 1.77)	(14.63, 3.11)	(8.54, 2.66)	(8.02, 3.93)	(2.92, 1.92)
Lifetime	(0.7, 0.8)	(0.68, 0.77)	(0.54, 0.78)	(0.6, 0.74)	(0.59, 0.78)	(0.76, 0.82)
Setup Time	(4.0, 3.8)	(3.8, 4.2)	(10.6, 29.4)	(14.6, 36.2)	(11.3, 37.0)	(3.79, 3.67)

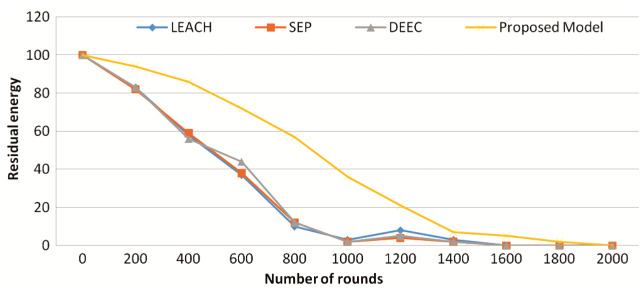

Fig. 9 — Round vs. Residual energy with energy: (0.3, 0.9)

Performance of Throughput

The proposed research is experimented with by applying various protocol schemes, and the obtained performance measures with the throughput for the energy values {0.4, 0.8, (0.4, 0.8)} are given in Table 1. The model has experimented with the startup energy level as 0.4, and the results are specified in Table 1.[(7–10)] The higher throughput (in percentage) is achieved for all the intervals in the devised model. The optimization of cluster head choice has been done based on the base station distance, the node's energy, and the node's energy efficiency. The reliability of the long-distance nodes is increased during the data transmission by modifying the size of the area of the candidate set of nodes. In contrast, near-distance nodes' energy consumption is reduced.

Analysis of Static & Dynamic Instances

The simulations of the static and the dynamic wireless instances in the form (static, dynamic) are shown in Table 2. Some wireless sensor nodes collect the sensing data with a single sink node in static networks. In the dynamic networks, 12% of the source nodes are set to detect the movable events, and the corresponding data has been sent to the single sink node. From the table, it has been concluded that the network instances consume less energy compared to other schemes. The model achieves a better throughput such that the source node transmits the sensing data efficiently to the sink. The valid sensing data transmission is done with a small amount of energy. The expected variance of energy consumption of the entire network is the standard deviation of the energy. The quick local convergence in path detectionis eliminated in the proposed model with pseudo-random choice. For large-scale networks, better lifetime and setup time measures are obtained due to more sensor nodes and pseudo-random choice route detection. The model's limitations are as follows: identification of small fluctuations and collisions in the dynamic case due to sensor nodes' movement.

Conclusions

To rightly balance the energy consumption in wireless networks, this research calculated the required clusters and network lifetime with different energy levels. The maximum lifetime is attained for α = 0.1. When α ranges from 0.3 to 0.6, there is a delay in initial node's death. The clustering protocol obtains the energy balance consumption by considering different criterion. The devised method puts a significant delay on the starting node based on the analysis of nodes' live location and the energy level of the cluster heads. The optimization of cluster head choice has been done based on – base station distance, node energy, and its energy efficiency. When the energy lies in (0.3, 0.9), the model obtained significant measures over the other strategies. The limitation of the model is when long-distance nodes are increased, reliability is affected. In future, the model is extended for large-scale applications to achieve high reliability and sustainability.

Conflict of Interest:

The authors declare no conflict of interests regarding the publication of this paper.

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