İSTANBUL UNIVERSITY CERRAHPAŞA

RESEARCH ARTICLE

Electrica 2021; 21(1): 41-49

Energy-Efficient Clustering-Based Mobile Routing Algorithm For Wireless Sensor Networks

Baybars Karabekir[1], Muhammed Ali Aydın[2], Abdül Halim Zaim[3]

[1]Department of Computer Engineering, İstanbul Commerce University, İstanbul, Turkey
[2]Department of Computer Engineering, İstanbul University - Cerrahpaşa Faculty of Engineering, İstanbul, Turkey
[3]Department of Computer Engineering, İstanbul Commerce University, İstanbul, Turkey

Cite this article as: Karabekir B, Aydın MA, Zaim AH. Energy-Efficient Clustering-Based Mobile Routing Algorithm For Wireless Sensor Networks. *Electrica,* 2021; 21(1): 41-49.

ABSTRACT

In this paper, we propose and investigate two types of algorithms for improving energy efficiency in wireless sensor networks. Clustering sensors in wireless sensor networks is considered an effective approach to prolonging network lifetime. In this paper, we divide the study area into clusters at 30-m2 intervals. In each cluster, the sensor that is the closest to the cluster center and has the highest residual energy is selected as the cluster head. In addition, a mobile sink is used to reduce the energy consumption of the cluster heads. The mobile sink travels to all clusters starting with the nearest cluster and collects data from the cluster heads. In the first model, cluster head selection is performed and the mobile sink route is calculated using a greedy approach. In the second model, cluster head selection is performed using an artificial neural network, and the mobile sink route is calculated using a greedy approach. We compared our models with the energy-efficient scalable routing algorithm by the first node dies parameter, all nodes die, and the residual energy of the network for each round condition. The simulation results demonstrated that the proposed models improved the energy efficiency and extended the network lifetime.

Keywords: Energy efficiency, LEACH, wireless sensor network

Introduction

Recent developments in sensor technology have allowed measured data to be transferred to a target area via wireless communication. The measured values are obtained as electrical signals and transmitted over long distances using wireless technologies [1, 2]. With the combination of hundreds of wireless detection devices, called sensor nodes, for a specific task, a network structure called a wireless sensor network (WSN) can be established. The task of a sensor network is to detect environmental information in a relevant area and send it to a central location called a base station (BS) or sink, where monitoring is performed [3].

Most sensors in a WSN work with batteries as an energy source, and charging or replacing these batteries is not possible in most scenarios. However, data transmission in a WSN involves high energy consumption. It is thus important to solve the energy efficiency problem in WSNs to be able to collect data for a long time and transmit them within the network [4].

The sensor clustering strategy is a method used to increase the energy efficiency of WSNs by balancing energy consumption. In this setup, sensors are divided into clusters according to specified parameters [5]. Cluster head (CH) nodes are responsible for collecting data from the cluster members (CMs) and transmitting them to the target node or BS. Choosing the appropriate candidate to be the CH among the nodes in each cluster is challenging, as the CH must fulfill the task of receiving data from the remaining nodes, collecting data, and sending the collected data to the BS or sink [6]. Because having the role of the CH is an energy-consuming process, a single node cannot be continuously in the CH role. Therefore, it is important to replace CHs at the appropriate intervals.

In scenarios in which the BS is stationary, sensors close to the BS serve as relays. Therefore, CHs near the target consume energy very quickly and create energy holes in the sensor network.

Corresponding Author:
Baybars Karabekir

E-mail:
baybars_karabekir@yahoo.com.tr

Received: 02.04.2020

Accepted: 17.09.2020

DOI: 10.5152/electrica.2021.20035

Using BS mobility is considered an effective method to alleviate this problem [7-9].

The remainder of this paper is organized as follows. Section 2 reviews related work on clustering routing protocols to optimize the energy problem, while Section 3 presents the models used and the CH selection method. Section 4 describes our proposed models, while Section 5 presents the performance evaluation and results. Finally, Section 6 presents the conclusions and discusses future work.

Related Works

The clustering strategy is a scheme aimed at improving the energy efficiency of WSNs by balancing energy consumption. This strategy organizes nodes into independent clusters whose nodes are geographically close together, and logically divides the network topology into a hierarchical structure [10].

In general, there are two types of roles in the network: CH and CM. The clustering algorithm plays an important role in saving power for an energy-constrained network. Selecting an appropriate CH can balance the load on the network, thereby reducing energy consumption and prolonging the network›s lifetime [2].

The primary goal of the routing algorithm design for a WSN is to improve energy efficiency to maximize the network lifetime. To achieve this goal, directing data traffic in a way that balances energy consumption in proportion to the existing energy between nodes is more important than minimizing the absolute energy consumed [11].

Among clustering algorithms, low-energy adaptive clustering hierarchy (LEACH) is a classic protocol used for hierarchical routing of data. The network is grouped into clusters, and the sensor nodes transmit their data to the sensor node whose role is the CH. The protocol selects CH nodes randomly for each round, and the CH node communicates with each CM to collect the detected data. The CH assigns time-division multiple access (TDMA) programs to the relevant CMs. The CMs can transmit data over the allotted time frame and reduce energy consumption by switching between an active and sleep status based on the time intervals allocated by the CH. In the LEACH protocol, only CHs can communicate with the BS or sink. Since the data are transmitted over the CHs, CHs consume energy in a short amount of time [2].

Selecting a CH is complex, as several factors must be considered for selecting the best node in the cluster, such as the distance between nodes, residual energy, mobility, and efficiency of each node. The LEACH algorithm extends the lifetime of the network; however, it has many limitations. For example, the selection n of CHs is performed randomly. That is, nodes with low energy and nodes with high energy have the same probability of being selected as the CH. Therefore, when a low-energy node is selected as a CH, it will consume energy more quickly due to the intensive processing [12].

There are many studies on the LEACH protocol in the literature [11-16]. LEACH works with a random selection of CH in each round, and the selected CH cannot be re-selected in the next round. In their study, Behera et al. [12] set a threshold value to re-select CH for the next round. The residual energy of the CH selected at the beginning of the tour is calculated and compared with the threshold value. If it is larger than the threshold value, the CH is selected again in the next round. However, IoT LEACH (I-LEACH) assumes single-hop communication. In large-scale WSNs, the distance between the CHs and BS may be large, which signifies high energy consumption in forwarding information to the BS. Thus, CHs consume energy more rapidly.

Ogundile et al. [11] proposed the mobile sink selective-path priority table (MSPT) algorithm, which attempts to balance the energy consumption in WSNs, thus preserving the life and functionality of the network for a reasonable period. In the first phase of the MSPT algorithm, which consists of two stages, CH selection is performed. In the second phase of the algorithm, the nodes choose an alternative path by selecting two nodes closest to them in the cluster. According to the total energy, energy range, energy ratio, and energy percentage characteristics, the priority table (PT) cost calculation is performed, which is the energy cost table. In the third phase, the calculated PT values are entered into the matrix, and the route information with the minimum value is selected. The major drawback of this paper, however, is that it does not mention how the cluster and CH selection are decided.

Elsmany et al. [13] proposed a three-layer hierarchical structure to reduce the burden of CHs in their proposed energy-efficient scalable routing algorithm (EESRA). In the setup phase, the random selection used in the LEACH protocol is applied for the selection of the cluster. After the CH selection, clusters are created. Each CH has the choice of one or more cluster congregations (CGs). The task of the CG is to collect data from the CMs and transmit them to CH. In the steady-state phase, the CMs transmit the data they perceive to the CG using carrier-sense multiple access with collision avoidance. The CG completes the tour by transmitting the collected data to the CH using TDMA. The results of the paper indicate that the proposed method improves the energy efficiency.

Sharma et al. [14] proposed energy-efficient clustering based on fuzzy c-means and differential evolution. The clustering process is performed by the BS. In this way, nodes are prevented from consuming energy for clustering. A load-balanced cluster is created with the fuzzy C means (FCM) algorithm by calculating the optimal cluster number in the network. The best node, CH, is selected according to the suitability calculated by the evolutionary algorithm in each node. However, single-hop communication used for data transmission and a fixed BS limit the network lifetime and functionality of a large-scale network.

Behera et al. [15] proposed the residual energy based LEACH (R-LEACH) protocol, which is a hierarchical clustering algorithm consisting of two steps. In the proposed structure, the initial energy aims to select the CH taking into account important parameters, such as the remaining energy of the individual node and the optimal number of CHs in the network. During the setup phase, the CHs and clusters are created using the LEACH algorithm. At the end of the round, the new CH is selected based on the residual energy of the remaining nodes. In the steady-state phase, each node transmits its data to the CH during the time assigned to it. After all the nodes in the cluster have finished transferring data, the CH completes the tour by processing the data and transmitting them to the BS with one or multiple hops. In large-scale WSNs, intra-cluster distances may increase. In this case, the energy consumption of the nodes can be rapid.

In addition to the CH and CM roles, Lin et al. [16] proposed a third role called the backup cluster head (BCH). After the sensors in the network are clustered, the node with the highest energy is selected as the CH. The CH examines the energies of the CMs in its cluster and then selects the node with the highest energy as the BCH. The CH collects data from the CMs in TDMA time frames. At the end of each round, the energy ratios between the CH and BCH are compared. The node with the highest energy between CH and BCH is assigned as new CH, thus ensuring energy efficiency. The main drawback of this paper, however, is that the network performance of large-scale WSNs is not reported.

Padmanaban et al. [17] proposed a simple and effective energy-efficient structural clustering algorithm for environmental monitoring areas. CHs are selected based on the average communication distance and remaining energy. The proposed algorithm significantly reduces the energy consumption by rotating the CH role between nodes at appropriate intervals.

Rajeswari et al. [18] proposed a cluster-based error tolerance technique using a genetic algorithm. The network is clustered according to an energy-saving distance-based clustering algorithm. For each CH, a series of backup nodes are selected using a genetic algorithm based on the coverage and residual energy parameters.

Nayak et al. [19] proposed a fuzzy logic-based clustering algorithm in the type 2 fuzzy logic (T2FL) model. In the proposed structure, the entire sensor network is divided into levels, and at each level, an efficient CH node is selected based on the T2FL model. Three fuzzy identifiers are discussed, such as the remaining battery power, distance to the BS, and concentration.

In the mobility-based clustering protocol proposed by Deng et al. [20] for WSNs with mobile nodes, the sensor node selects itself as the CH based on its remaining energy and mobility. CM nodes are allocated a time frame for data transmission in ascending order in the TDMA schedule. In the steady-state phase, a sensor node transmits its detected data over time. In addition, Zhang et al. [21] proposed an energy-efficient central clustering method. This method uses a central control algorithm to create an improved CH set with less mobility and more energy. The general problem of the methods proposed in [17-21] is, single-hop communication used for data transmission limit the network lifetime and functionality of a large-scale network. In this paper, we propose a mobile routing algorithm with low energy and an adaptive clustering hierarchy. In our model, we use single-hop transmission for both intra- and inter-cluster communication. In addition, we separate clusters from each other at a constant interval according to an optimal Bluetooth Low Energy (BLE) connection distance. In this way, we model a scalable WSN. In addition, we use a mobile sink to collect data from CHs, thereby minimizing the distance between the CHs and sink to reduce the energy consumption. The proposed model provides a way to maintain the network lifespan in spite of increases in the network size. In this paper, we evaluate the proposed model against the EESRA in terms of network performance with respect to changes in the network size.

Models and CH Selection

Network Model

In our proposed model, we use BLE sensors, which we assume are randomly distributed in a two-dimensional area, and their locations are constant throughout the network's life cycle. The sensors have the same initial value, and each sensor has a Global Positioning System sensor. The sensors report location and energy information to the mobile sink while the energy consumption is ignored. The packet size is set to a fixed value as in the simulation parameters. The area is divided into sections by the mobile sink at intervals of 30 m^2, and sensors in each section form a cluster. The mobile sink decides which node in the cluster becomes the CH. This decision is repeated in every round. The information obtained by the CMs is transferred to the CH, and data collected by the CH are transferred to the mobile sink.

Energy Model

The energy used to transfer *k*-bit data to a point at distance *d* and to receive *k*-bit data from a point at distance *d* is calculated using the first order radio model specified in (3) and (4), respectively E_{lec}. refers to energy consumption for *k*-bit data during sending or receiving E_{amp}. is the transmission parameter, and E_{DA} refers to the energy consumption for data aggregation. The parameter values used in our models are listed in Table 1.

CH Selection

In this study, nodes within every 30 m^2 form a cluster, as illustrated in Figure 1. In the cluster, a node evaluates its distance from the cluster center and its residual energy. The node that is closest to the cluster center and has the highest residual energy is selected as the CH.

For each sensor, the distance between its location and center is calculated by the Euclidean distance defined as follows (1):

$$dist = \sqrt{(x_{node} - x_{center})^2 + (y_{node} - y_{center})^2} \tag{1}$$

Table 1. Simulation parameters

Symbol	Description	Value
A	Network size	90 m x 90 m, 120 m x 120 m
n	Total number of sensor nodes	100,200
E_0	Initial energy of nodes	2 J
E_{DA}	Energy dissipation: aggregation	5 nJ/bit
E_{amp}	Energy dissipation: power amplifier	10 pJ/bit
E_{elec}	Energy consumed to run the transmitter or the receiver circuit per bit	50 nJ/bit
k	Data size of packet	4,000 bits

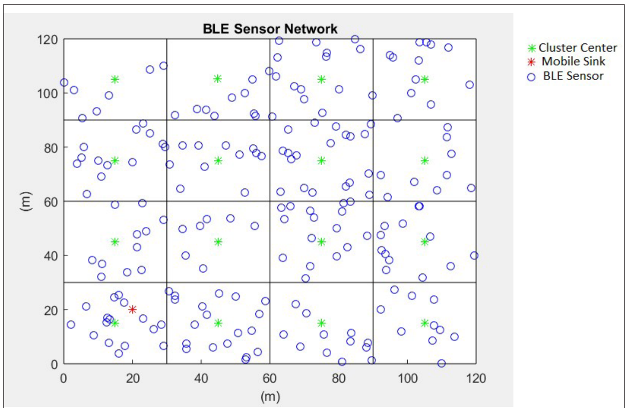

Figure 1. Clustering with 30- m² intervals according to BLE communication distance

Due to the wide range of calculated distance values, to obtain more accurate results in the selection of the CH, we reduce the lengths based on the cluster to the range of [0,1] using min-max normalization.

$$n\_dist = \frac{dist_{node} - min_{dist}}{max_{dist} - min_{dist}}, \tag{2}$$

where $dist_{node}$ is the distance between the node and cluster center, min_{dist} is the value of the node at the minimum distance from the cluster center, and is the value of the node at the maximum distance from the cluster center.

The energy consumed by the CM to send data is as follows:

$$E_{TX}(k,d) = E_{elec} * k + \mathrm{E}_{amp} * k * d^2 \quad , \tag{3}$$

where E_{tec} is the per-bit energy consumption by the receiver or transmitter, is the data size of the package, E_{amp} is the amplifier parameter, and d is the distance [14].

The energy consumed by the CH to receive the sent data is as follows:

$$E_{RX}(k,d) = (E_{elec} + E_{DA}) * k \ , \tag{4}$$

where E_{DA} is the energy consumption for data aggregation [14].

The energy consumed by the CH to transfer the collected data to the BS is as follows [14]:

$$E_{TX}(k,d) = (E_{elec} + E_{DA}) * k + \mathrm{E}_{amp} * k * d^2 \ . \tag{5}$$

The residual energy of the sensor node is as follows:

$$E_{residual} = E_0 - E_{total} \, , \tag{6}$$

where E_0 is the initial energy of the node, and E_{total} is the energy consumed by the node [14].

According to (7), the node with the highest f value is selected as the CH:

$$f = (E_{residual} - n\_dist) \tag{7}$$

Proposed Model

We discuss two different approaches for energy-efficient cluster-based mobile routing in mesh networks consisting of BLE sensors. Each approach consists of three parts. In the first part, clustering and CH selection are performed. In the second part, the mobile sink travels around the cluster centers and starts the third part for each cluster that it reaches. In the third part, the CMs transfer their data to the CH, and the CH transmits the collected data to the mobile sink.

Clustering and Mobile Routing with Greedy Approach (CMR)

In the first approach, a plane consisting of sensors distributed randomly in the relevant area is divided into pieces at 30-m intervals, as illustrated in Figure 1, and the mobile sink forms a cluster within every 30 m². The node with the highest residual energy and close to the cluster center is selected as the CH in the cluster. This structure corresponds to the master mode in BLE sensors. After the cluster is created and the CH is selected, the mobile sink moves to the center of the nearest cluster. When the mobile sink reaches the center of the cluster, the CMs send the data they receive from the environment to the CH. The CH transmits the data it collects to the mobile sink. When the transfer process in the cluster is completed, the mobile sink moves to the next cluster and repeats the data collection process. Table 2 presents the CMR algorithm.

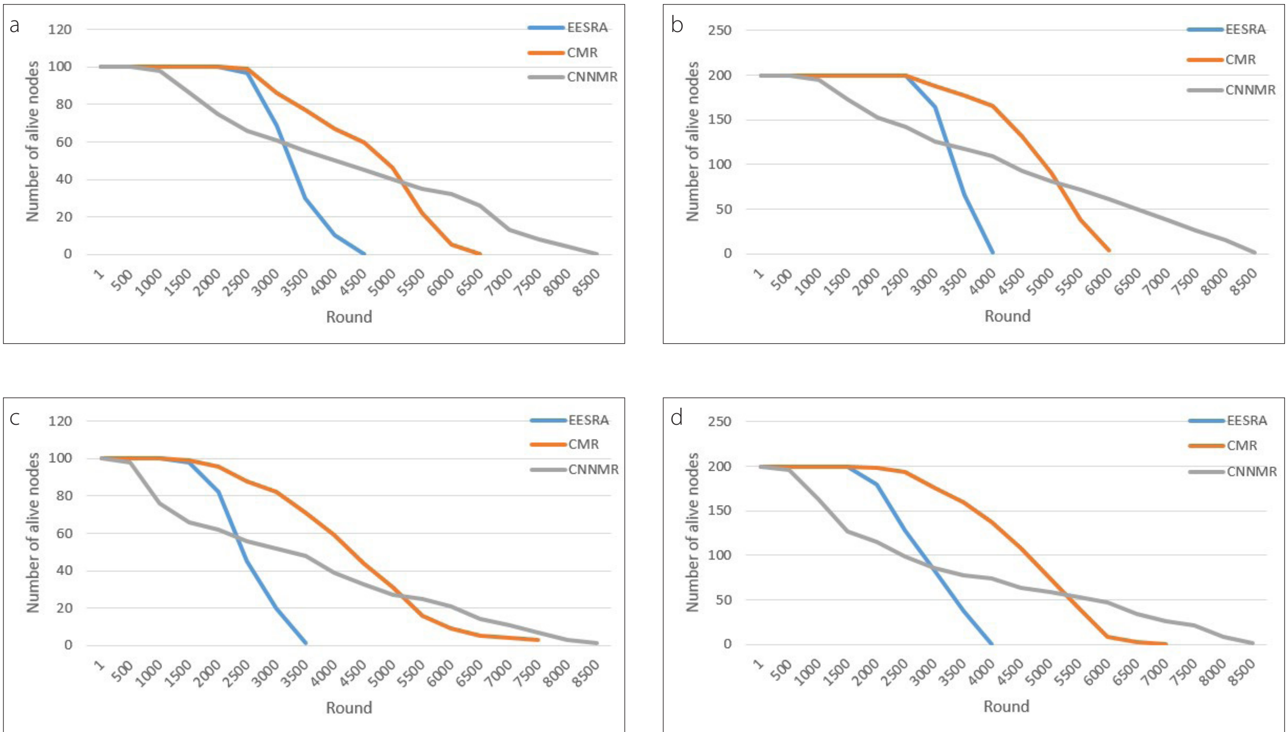

Figure 2. a-d. Number of alive nodes per round for: (a) 90 m x 90 m, 100 nodes; (b) 90 m x 90 m, 200 nodes; (c) 120 m x 120 m, 100 nodes; (d) 120 m x 120 m, 200 nodes

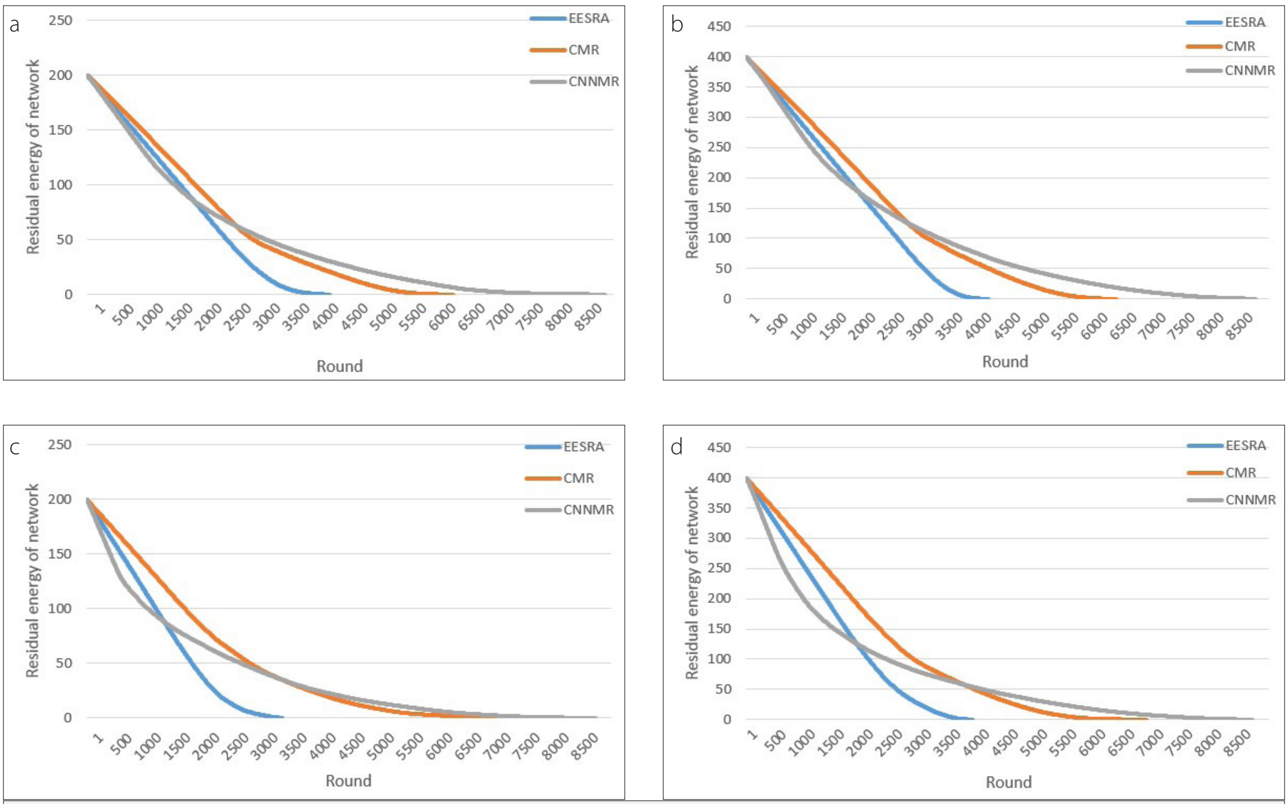

Figure 3. a-d. Residual energy of network per round for: (a) 90 m x 90 m, 100 nodes; (b) 90 m x 90 m, 200 nodes; (c) 120 m x 120 m, 100 nodes; (d) 120 m x 120 m, 200 nodes

Table 2. CMR algorithm

Initialization of network and parameters
Establishing of the clusters within 30 meter square
while alive nodes > 0
compute distance and establish mobile sink route
for each cluster
establish the operation of next cluster
for each cluster member
compute the distance according to (1)
compute residual energy according to (6)
end for
min-max normalization for cluster according to (2)
cluster head selection according to (7)
for each cluster member
if node = cluster member
compute energy consumption according to (3)
else if node= cluster head
compute energy consumption according to (4,5)
end if
update residual energy
if residual energy <= 0
node is dead update the alive node
end if
end for
end while

CMR: Clustering and Mobile Routing with Greedy Aproach

Clustering with Artificial Neural Network and Mobile Routing with Greedy Approach (CNNMR)

In the second approach of our study, we divide the relevant study area into parts at 30-m intervals, as performed in the first approach. In the same way, the mobile sink forms a cluster within every 30 m^2. For the artificial neural network used in the model, we provide the x and y coordinates and residual energy information of the sensor nodes as input. We determine the CH node using an artificial neural network trained with the sample input values within the cluster. This structure corresponds to the master mode in BLE sensors. After the cluster is created and the CH is selected, the mobile sink moves to the center of the nearest cluster and repeats the same steps for data collection as in the first approach. Table 3 presents the CNNMR algorithm.

Performance Evaluation and Results

To evaluate the proposed models, we benchmarked them against EESRA. We focused on assessing the energy efficiency considering four scalability case studies with 100 and 200 nodes for a 90-m^2 area and 100 and 200 nodes for a 120-m^2 area. We compared our models with EESRA in terms of the timespan from the start of the network operation to when the first node dies (FND), the timespan to reach the all nodes depleted (AND) condition, and the residual energy of the network for each round. We ran our method ten times with the simulation parameters presented in Table 1. In each run, we randomized the sensor nodes.

The sensors were randomly distributed for each run, and the same sensor set was used in all three models for comparison in each run. The mobile sink position was fixed at 20 m x 20 m with unlimited energy, and all nodes started with an initial energy of 2 J. In this study, the packet size was set to 4,000 bits. The simulation was performed using MATLAB (MathWorks, Natick, MA, USA).

Here, we present the simulation results of the proposed CMR and CNNMR models in comparison with the EESRA protocol using the same simulation parameters as in Table 1. The models were evaluated in terms of the number of alive nodes per round and the residual energy of the network per round.

With an increase in the number of rounds, the sensor node depleted its energy and eventually died. Figure 2 demonstrates the number of alive nodes per round for four cases. In Figure 2(a), after the completion of 4,304 rounds, the number of active nodes decreased to zero for EESRA, while the number of rounds reached 6,372 for CMR and 9,052 for CNNMR.

Other simulation results are as follows. In Figure 2(b), which pertains to 200 nodes for a 90-m^2 area, 4,217 rounds were reached for EESRA, 6,161 rounds were reached for CMR, and 8,584 rounds were reached for CNNMR. In Figure 2(c), which pertains to 100 nodes for a 120-m^2 area, 3,516 rounds were reached for EESRA, 8,025 rounds were reached for CMR, and 8,915 rounds were reached for CNNMR. In Figure 2(d), which pertains to 200 nodes for a 120-m^2 area, 3,949 rounds were reached for EESRA, 6,843 rounds were reached for CMR, and 8,774 rounds were reached for CNNMR.

The simulation results thus clearly indicate that the proposed CNNMR model offered superior performance to CMR and EESRA in terms of the alive nodes versus transmission rounds. Likewise, the CMR model exhibited better performance than EESRA.

The residual energy of the network per round for four cases is presented in Figure 3. A comparison of the results indicates that CMR and CNNMR used less energy than EESRA for the four different scenarios. In addition, comparing CMR and CNNMR reveals that CNNMR led to lower energy consumption in the network.

Table 3. CNNMR algorithm

Initialization of network and parameters
Establishment of clusters within 30 m2
while alive nodes > 0
compute distance and establish mobile sink route
for each cluster
establish the operation of the next cluster
train the network with test input and test target data
run the trained network for the cluster
set the max value in the output as the cluster head
for each cluster member
if node = cluster member
compute energy consumption according to (3)
else if node = cluster head
compute energy consumption according to (4) and (5)
end if
update residual energy
if residual energy <= 0
node is dead, update the alive node
end if
end for
end while

CNNMR: Clustering with Artificial Neural Network and Mobile Routing with Greedy Approach

Table 4 presents the FND and AND values in the simulation run for all three models. A comparison of the results for all scenarios demonstrates that the CNNMR model reached the FND value the fastest. However, upon observing the overall network, the CNNMR model had the best performance compared to the largest AND value.

From the above analysis, it is clear that the proposed models demonstrate better performance for both small and large areas with sparsely as well as densely populated networks.

Conclusions and Future Work

In this study, we proposed an energy-efficient clustering-based mobile routing algorithm based on the LEACH protocol. First, we divided the study area into clusters at 30-m^2 intervals. For each cluster, we selected the CH with two different models using a greedy algorithm and artificial neural network. With the greedy approach, the shortest distance between the mobile sink and cluster centers was determined. Using that route, the mobile sink moved to the clusters and collected data. The simulation results revealed that CMR and CNNMR extended the network's lifespan to a greater extent than EESRA. In future work, we will realize the route drawn for the mobile sink with a genetic algorithm. In addition, we will compare CMR and CNNMR with new models.

Table 4. Comparison of EESRA, CMR, and CNNMR

Area	Node Number	Protocol	FDN	AND
90 m x 90 m	100	EESRA	2222	4304
		CMR	2227	6372
		CNNMR	894	9052
90 m x 90 m	200	EESRA	2528	4217
		CMR	2472	6161
		CNNMR	848	8584
120 m x 120 m	100	EESRA	1306	3516
		CMR	1246	8025
		CNNMR	443	8915
120 m x 120 m	200	EESRA	1547	3949
		CMR	1934	6843
		CNNMR	449	8774

Peer-review: Externally peer-reviewed.

Conflict of Interest: The authors have no conflicts of interest to declare.

Financial Disclosure: The authors declared that the study has received no financial support.

References

1. C. Ma, W. Liang, M. Zheng, H. Sharif, "A connectivity-aware approximation algorithm for relay node placement in wireless sensor networks," IEEE Sensors Journal, vol. 16, no. 2, pp. 515-528, 2015. [Crossref]
2. Z. Fei, B. Li, S. Yang, C. Xing, H. Chen, L. Hanzo, "A survey of multi-objective optimization in wireless sensor networks: Metrics, algorithms, and open problems," IEEE Communications Surveys & Tutorials, vol. 19, no. 1, pp. 550-586, 2016. [Crossref]
3. S. Verma, P. Ranar, C. Gupta, "Efficient energy optimization in Wireless Mesh Network using cluster point," In 2015 1st International Conference on Next Generation Computing Technologies (NGCT), pp. 135-138, 2015. [Crossref]
4. P. Kashtriya, R. Kumar, G. Singh, "Energy Optimization Using Game Theory in Energy-Harvesting Wireless Sensor Networks," In 2018 First International Conference on Secure Cyber Computing and Communication (ICSCCC) , pp. 472-476, 2018. [Crossref]
5. P. Nayak, A. Devulapalli, "A fuzzy logic-based clustering algorithm for WSN to extend the network lifetime," IEEE sensors journal, vol. 16, no. 1, pp. 137-144, 2015. [Crossref]

6. Y. Zhou, N. Wang, W. Xiang, "Clustering hierarchy protocol in wireless sensor networks using an improved PSO algorithm," IEEE Access, vol. 5, pp. 2241-2253, 2015. [Crossref]
7. T. A. Al-Janabi, H. S. Al-Raweshidy, "A centralized routing protocol with a scheduled mobile sink-based AI for large scale I-IoT," IEEE Sensors Journal, vol. 18, no. 24, pp. 10248-10261, 2018. [Crossref]
8. M. Abo-Zahhad, S. M. Ahmed, N. Sabor, S. Sasaki, "Mobile sink-based adaptive immune energy-efficient clustering protocol for improving the lifetime and stability period of wireless sensor networks," IEEE Sensors Journal, vol. 15, no. 8, pp. 4576-4586, 2015. [Crossref]
9. M. Krishnan, Y. M. Jung, S. Yun, "An Improved Clustering with Particle Swarm Optimization-Based Mobile Sink for Wireless Sensor Networks," In 2018 2nd International Conference on Trends in Electronics and Informatics (ICOEI), pp. 1024-1028, 2018. [Crossref]
10. J. Singh, P. Sahni, S. Kaur, "Nature Inspired Approach based Energy Optimization using Dynamic Clustering in Wireless Sensor Networks," In 2018 International Conference on Computing, Power and Communication Technologies (GUCON), pp. 671-675, 2018. [Crossref]
11. O. O. Ogundile, M. B. Balogun, O. E. Ijiga, E. O. Falayi, "Energy-balanced and energy-efficient clustering routing protocol for wireless sensor networks," IET Communications, vol. 13, no. 10, pp. 1449-1457, 2019. [Crossref]
12. T. M. Behera, U. C. Samal, S. K. Mohapatra,"Energy-efficient modified LEACH protocol for IoT application," IET Wireless Sensor Systems, vol. 8, no. 5, pp. 223-228, 2018. [Crossref]
13. E. F. A. Elsmany, M. A. Omar, T. C. Wan, A. A. Altahir, "EESRA: Energy Efficient Scalable Routing Algorithm for Wireless Sensor Networks," IEEE Access, vol. 7, pp. 96974-96983, 2019. [Crossref]
14. R. Sharma, V. Vashisht, U. Singh "EEFCM-DE: energy-efficient clustering based on fuzzy C means and differential evolution algorithm in WSNs," IET Communications, vol. 13, no. 8, pp. 996-1007, 2019.[Crossref]
15. T. M. Behera, S. K. Mohapatra, U. C. Samal, M. S. Khan, M. Daneshmand, A. H. Gandomi, "Residual Energy Based Cluster-head Selection in WSNs for IoT Application," IEEE Internet of Things Journal, 2019. [Crossref]
16. D. Lin, Q. Wang, "An Energy-Efficient Clustering Algorithm Combined Game Theory and Dual-Cluster-Head Mechanism for WSNs," IEEE Access, vol. 7, pp. 49894-49905, 2019. [Crossref]
17. Y. Padmanaban, M. Muthukumarasamy, "Energy-efficient clustering algorithm for structured wireless sensor networks," IET Networks, vol. 7, no. 4, pp. 265-272, 2018. [Crossref]
18. K. Rajeswari, S. Neduncheliyan, "Genetic algorithm based fault tolerant clustering in wireless sensor network," Iet Communications, vol. 11, no. 12, pp. 1927-1932, 2017. [Crossref]
19. P. Nayak, B. Vathasavai, "Energy efficient clustering algorithm for multi-hop wireless sensor network using type-2 fuzzy logic," IEEE Sensors Journal, vol. 17, no. 14, pp. 4492-4499, 2017. [Crossref]
20. S. Deng, J. Li, L. Shen, "Mobility-based clustering protocol for wireless sensor networks with mobile nodes," IET wireless sensor systems, vol. 1, no. 1, pp. 39-47, 2011. [Crossref]
21. J. Zhang, R. Yan, "Centralized Energy-Efficient Clustering Routing Protocol for Mobile Nodes in Wireless Sensor Networks," IEEE Communications Letters, 2019. [Crossref]
22. X. Li, B. Keegan, F. Mtenzi, T. Weise, M. Tan, "Energy-Efficient Load Balancing Ant Based Routing Algorithm for Wireless Sensor Networks," IEEE Access, vol. 7, pp. 113182-113196, 2019. [Crossref]
23. J. W. Lee, J. J. Lee, " Ant-colony-based scheduling algorithm for energy-efficient coverage of WSN," IEEE sensors journal, vol. 12, no. 10, pp. 3036-3046, 2012. [Crossref]
24. D. Qin, J. Ma, Y. Zhang, P. Feng, P. Ji, T. M. Berhane, "Study on Connected Target Coverage Algorithm for Wireless Sensor Network," IEEE Access, vol. 6, pp. 69415-69425, 2018. [Crossref]
25. C. M. Yu, M. L. Ku, H. K. Lin, "A Hybrid Mesh-Ring Topology for Bluetooth Networks," In 2018 IEEE 5G World Forum (5GWF) pp. 520-523, 2018.
26. S. Chand, B. Kumar, "Genetic algorithm-based meta-heuristic for target coverage problem," IET Wireless Sensor Systems, vol. 8, no. 4, pp. 170-175, 2018. [Crossref]
27. L Sayad, D. Aissani, L. Bouallouche-Medjkoune, "Placement optimization of wireless mesh routers using firefly optimization algorithm," In 2018 International Conference on Smart Communications in Network Technologies (SaCoNeT), pp. 144-148, 2018. [Crossref]
28. C. C. Lin, L. Shu, D. J. Deng, "Router node placement with service priority in wireless mesh networks using simulated annealing with momentum terms," IEEE Systems Journal, vol. 10, no. 4, pp. 1402-1411, 2014. [Crossref]
29. K. Derr, M. Manic, "Wireless sensor networks-Node localization for various industry problems," IEEE Transactions on Industrial Informatics, vol. 11, no. 3, pp.752-762, 2015. [Crossref]

Baybars Karabekir has been working in Software Development Departman as a IT Manager in Halkbank for 10 years. He has been studying for Doctor of Philosophy in Computer Engineering in Istanbul Commerce University. He received his B.Sc. degree in Computer Engineering from Istanbul Commerce University in 2009 and M.Sc. degree in Information Technology from Galatasaray University in 2011.

Muhammed Ali Aydin is currently working as an associate professor at Computer Engineering Department of Istanbul University-Cerrahpasia. His interest mainly focuses on Cyber Security, Cryptography, Network Security and Communication- Network Protocols. He received his B.Sc. degree in Computer Engineering from Istanbul University in 2001, M.Sc. degree in Computer Engineering from Istanbul Technical University in 2005 and PhD degree in Computer Engineering from Istanbul University in 2009 and he has completed Post Doctoral research at Telecom SudParis in Department of Computer Science.

Abdül Halim Zaim is currently a faculty member in the Department of Computer Engineering at the Faculty of Engineering and Design at Istanbul Commerce University, a faculty member in the Department of Computer Engineering at the Faculty of Engineering at Istanbul University and the Director of the Center for Information Technology Application and Research at Istanbul Commerce University. Abdul Halim Zaim served as Vice Rector and Vice President of Academic Evaluation Commission at Istanbul Commerce University. He received his B.Sc. degree in Computer Engineering from Yıldız Technical University in 1993, M.Sc. degree in Computer Engineering from Bogazici University in 1996 and his PhD in Electrical and Computer Engineering from North Carolina State University (NCSU) in 2001.