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RESEARCH ARTICLE

Performance Evaluation of Modified Distributed Energy Efficient based Clustering Aggregation algorithm in Wireless Sensor Networks

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Abstract

Objective: To reduce energy consumption and robust algorithm for Wireless Sensor Networks (WSNs). To achieve energy-efficiency, the proposed algorithm incorporates data aggregation models. Data aggregation involves combining and summarizing data from multiple sensor nodes before transmitting it to the Base Station (BS) which helps reduce the overall energy consumption of the network. **Methods:** A modified version of the Distributed Energy Efficient Clustering Algorithm (MDEECA) is proposed The MDEECA algorithm introduces several parameters which include scaling factor, selection of Cluster Head (CH), threshold probability, and information related to the neighborhood for the next CH selection. **Findings:** The proposed model is evaluated in terms of packet transmissions. In the first 1000 iterations, 9564 packets are sent to the BS, and this number increases to 29394 packets after 4000 iterations. In the case of packets sent to the CHs, 14456 packets are sent in the first 1000 iterations, and this increases to 112464 packets after 4000 iterations. These results demonstrate the effectiveness of the proposed MDEECA algorithm in terms of data transmission efficiency. **Novelty:** The modified MDEECA algorithm's novelty lies in its approach, CH selection based on the residual energy of nodes and the average energy of the network. This modification enhances robustness of the algorithm and improves energy performance, leading to an extended network lifetime. The modified MDEECA algorithm also increases the network lifetime and enhances energy performance in comparison to existing models.

Keywords: Network Protocols; Wireless Network; Sensor node

1 Introduction

In Wireless sensor networks (WSNs), a large amount of sensor nodes is deployed in certain interesting regions. The nodes are small and have characteristics such as computing element, communication, and sensing. Communication occurs via short radio signals to perform a common task. To communicate the gathered data to the sink node, an individual node consumes a large amount of energy. Instead, if data is collected and aggregated, energy consumption will be less while transmitting data to the sink node. Data aggregation implies collection and mixing significant information with specific region of interest and the related effectiveness depends on the techniques/approaches which are implemented. Effectiveness always enhances the knowledge of energy consumption which leads to an increase in the network lifetime.

In general, data aggregation process models the collection of data through various nodes. The data aggregation algorithms help to aggregate sensed data which originate from the sensor nodes. The output generated from the algorithm is the aggregated data which relies on an effective path being selected to transfer the data to an individual sink node. The best route to transfer the data is decided based on the routing protocol adopted in the WSN. However, multiple failures can occur due to energy, link, and coverage due to the presence of dynamic environment, where sensor nodes are deployed and cannot lie on a single path towards the source and destination. The simple concept of multipath in which, if one path fails then the transmission of data occurs on another path, can be implemented via a routing protocol which needs to be developed considering both energy consumption and data aggregation models. The effectiveness of data aggregation is based on developing the routing protocol. In the current article, we propose a technique which enhances life span of the network by reducing the consumption of energy by the nodes.

The Hybrid Distributed Hierarchical Agglomerative Clustering model involves both quality and quantity data to provide the information related to the location and connectivity of the node. The model aims to be economical due to the absence of GPS[(1)]. The routing process is performed using virtual clustering. The CH is chosen to have a specific location and residual power of the sensor nodes[(2)]. The routing protocol for heterogeneous network and adaptive threshold sensitive distributed energy efficient cross layer routing protocol for the routing process is discussed in[(3)]. The CH is chosen based on the weighted probability within the cluster. The authors in[(4)] presented a model based on the auto regressive method. The study considers various types of attacks which take place on WSN. The technique which is developed is based on bad mouthing attack. In[(5)], the authors developed the Hierarchical Energy Balancing protocol in WSN which provides the characteristics of load balancing and reduces energy consumption. The authors in[(6)] introduced optimal cluster-based technique for multi-hop to balance multiple mobile sinks. The proposed technique uses a heuristic approach in a geometrical manner. The utilization of reduced network energy, and quantization technologies are considered. In[(7)], the authors discussed the improved Harmony Search Based Energy Efficient Routing Algorithm for WSNs. The algorithm is based on harmony search in WSNs. The authors in[(8)] discussed the modified Mutual Exclusive Distributive Clustering protocol. The proposed model improves the reduction of energy consumption of CH nodes and life span of the WSN. In[(9)], the authors developed the energy aware distributed unequal clustering protocol to handle the issues of multi-hop. In the proposed method, the CH is elected based on the nodes which are deployed as neighbor. The authors in[(10)] introduced the P-LEACH algorithm to overcome the problems of LEACH and PEGASIS in terms of energy and power consumption. The P-LEACH algorithm is found to be the best routing algorithm and can be improved over PEGASIS and LEACH. In[(10)], the authors developed H- LEACH for the WSN which deals with the residual and maximum energy nodes whenever a CH is selected using threshold. The authors in[(11)] discussed PSO-Based Clustering Energy Optimization algorithm for clustering and selecting the CH. The technique is evaluated considering throughput, PDR, and network lifetime energy consumption as the metrics. In[(12)], the authors described hybrid swarm intelligence as the combination of ABC and ACO to resolve a NP in WSN. The authors in[(13)] developed a Gaussian mixture model in which few nodes transfer using the hop-to-hop mechanism in a distributed manner simultaneously reducing the number of iterations and increasing the rate of convergence. In[(14)], the authors described FuMAM to determine distance, energy, and several neighbors. The network is segmented using K-means, and the model performs better in regard to rate of successful MA and other parameters. The authors in[(15)] used non-uniform clustering to address the issue of energy holes. The PEGASIS and Hamilton loop algorithms are considered for single and multi-hop in WSN simultaneously inserting MA, and local optimization to evaluate the minimum distance coverage, energy consumption and lifetime of the network. In[(16)], the authors described fuzzy-based MA technique to determine distance, residual energy, and several neighbors. It is shown that FuMAM performs better when compared with MIP in view of success rate. The authors in[(17)] explained various redundancy issues which are the main reason for decrease in lifetime of the network.

Overall, the existing literature is based on a few existing models, and the majority of the research is directed towards the increase in lifetime of the network. Hence, we gather that there is a need to formulate a method which can serve this purpose and in addition, has a simpler design, is fast in performance, and economical.

2 Proposed Methodology

The modified distributed energy efficient clustering (MDEECA) algorithm is proposed in this section. The algorithm considers improvements in terms of energy and network lifetime are considered. Figure 1 shows the workflow of the proposed model.

Table 1. Comparative analyses of reviewed protocols

Technique/Description	**Advantages**	**Limitations**
Swarm Optimization-based Clustering algorithm to perform clustering and selection of CH in WSN.	Lifespan of the network increased.	Complex to implement the model in WSN.
Based on adaptive threshold sensitive distributed energy efficient cross layer routing protocol.	Increased Lifespan	Only reactive and proactive routing protocols are considered.
Time series trust methodology Auto regressive method based on trust model is developed for data aggregation.	Performance is increased	More overhead is created and leads to consumption of more energy.
Hybrid clustering H-DHAC applicable to data in form of qualitative and quantitative for aggregation of data in WSN	Less cost and there are no requirement of GPS	Poor performance in view of lifetime and transmission of data in WSN.

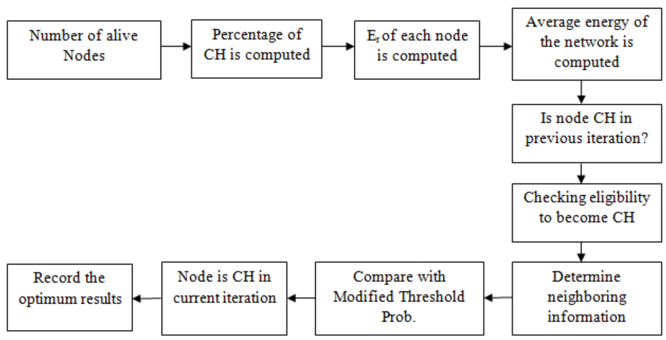

Fig 1. Proposed MDEECA model

The parameters such as energy and lifetime of the network, which majorly impact the proposed MDEECA model are discussed. A scaling factor is introduced to reduce energy consumption of the nodes within a cluster. To ensure direct communication to the BS, intra cluster communication is conducted with reduced power level. If the network layout has the size of 100m x 100m with 10 clusters, then the maximum power of intra cluster communication is limited to more than 100m x 100m. The scaling factor is calculated as[4].

$$\text{Scalling Factor } = \left\{ \text{rand } () X \frac{\text{Area of Netwrok Field}}{\text{Area of the cluster } X \text{ no.of nodes in a cluster}} \right\} \tag{1}$$

The threshold probability has much impact on the selection of CHs to determine whether nodes can become CH or not[17,18]. The modified mathematical equation to determine probability for the node to become a CH is[5]

$$Pi = \left\{ \frac{\text{Energy of the Network Field}}{\sum_{j=1}^{n} \text{ Total energy of all nodes within a cluster}} \right\} \tag{2}$$

In order to improve efficiency, total energy of all nodes within a cluster is considered and the equation is[5] .

$$T(Si) = \left\{ \left(\frac{Pi}{1 - Pi \left(r \bmod \frac{Pi}{\sum_{j=}^{n} nPi} \right)} \right\} \qquad if\ Si\ \varepsilon\ G \right.$$

$$0 \quad \text{Otherwise} \tag{3}$$

Each node calculates individual probability threshold to become CH. With the modified threshold probability, total energy within the cluster is considered for selecting the CHs. Therefore, the node which has the maximum residual energy in a cluster becomes a CH and improves the lifetime of network[19]. The neighborhood process is introduced to identify the next possible

CHs. The distance-based measure is applied on the current CH location to compute the location of the next CH. If energy of nodes is less than the current CH energy, then all the nodes are rejected; else, nodes are selected as neighbor of the CH. The nodes with highest energy can become neighbors of current CH. The proposed modified DEEC algorithm is detailed below.

Step 1: Initialize parameter includes network size, nodes, scale factor, live nodes and percentage of the CHs.

Step 2: Determine current energy of i^{th} node and energy of the current round using equation 4[6].

$$E_{\text{round}} = L\left(2NE_{\text{elec}} + NE_{DA} + k\varepsilon_{mp}d^4_{CHto\ BS} + N\varepsilon_{fs}d^2_{CHto\ BS}\right) \tag{4}$$

Step 3: Average energy of the network is computed using equation 5[7] , and residual energy is computed for sensor nodes to become CH using equation 6[7] .

$$\{E(r) = \frac{1}{N}E_{\text{total}}\left(1 - \frac{r}{R}\right) \tag{5}$$

$$n_i = \frac{1}{Pi} = \frac{\underline{E}(r)}{P_{opt}E_i(r)} = n_{opt}\frac{\underline{E}(r)}{E_i(r)} \tag{6}$$

Step 4: During the process, if sensor node is CH in last iteration, then node belongs to the set of CHs and is eligible to become a CH. It then determines the neighboring information of the selected CH; else, node is member of the CH and sends the data to appropriate CH.

Step 5: Next, energy of the selected node is compared to modified threshold probability to act as CH. If energy of the nodes is greater than threshold probability, then it acts as CH.

Step 6: Until maximum iteration is reached, repeat Steps 2-5.

Step 7: Obtain optimum results of the algorithm.

3 Results and Discussion

In this section, experiments for evaluating the proposed modified MDEECA model are conducted using MATLAB. The experiments are performed on a system which is core i5, has 4 GB RAM, and a Windows operating system. To assess performance of the proposed algorithm, various parameters are considered including stability period, data packets, and lifetime of the network. These parameters are measured and recorded to analyze the effectiveness of the proposed model. The results obtained from the proposed model are compared with different existing models to determine their superiority or improvements over existing approaches.

In the experiment setup, 100 nodes are randomly distributed within a 100m x 100m field, and their orientations are also randomized. It is assumed that all the nodes remain stationary throughout the experiment. Furthermore, the BS, which is likely to be central node in the network, is positioned at center of the field. Table 2 mentions settings of the radio network specifically for the heterogeneous networks. These settings are likely to include parameters such as transmission power, communication range, and other relevant parameters necessary for the experiment. This section highlights the comparison of proposed algorithms with existing models and provides specific details regarding the network setup in terms of node distribution, base station position, and radio network settings.

Table 2. Settings of radio networks for MDEECA Algorithm

Parameters and their Descriptions	Value
Network field	100mx100m
No. of nodes	100
Eelec (Radio Electronics energy)	5nJ/bit
Efs (Amplifiers energy for free space)	10pJ/bit/m2
Eamp (Amplifiers energy for multipath channel)	0.0013 pJ/bit/m2
E0 (Initial energy)	0.5J
EDA (Data Aggregation Cost)	0.5nJ/bit/message
D0	50m
Message Size	4000bits
Popt (Reference Probability for CHs)	0.1
EThreshold (Threshold energy)	E0/4

To evaluate performance of the proposed model, following performance parameters are adopted:

- stability of network (live and dead nodes)
- lifetime (number of nodes live throughout execution of the program)
- data packets (amount of data transfer through the BS)
- packets sent to BS (total number of packets sent from CH to BS), and
- packets sent to CHs (total number of packets sent through sensor nodes to CHs) are used.

The nodes which are considered to be distributed in the selected field is shown in Figure 2.

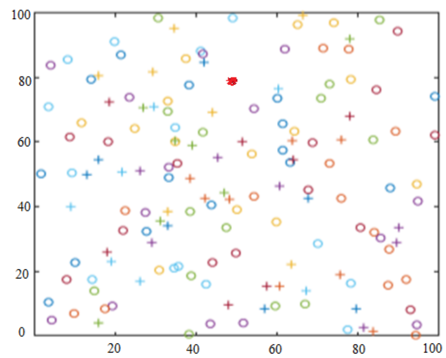

Fig 2. Node distribution in 100mx100m field with Base station

- Normal sensor nodes (60%)
- Base station

+ Advanced nodes (40%)

Figure 3 shows the graph of dead nodes with a variation of iteration of MDEECA model over 4000 iterations. It is observed that the nodes are alive up to 1600 iterations after which, the nodes start dying which verifies effectiveness of the proposed algorithm. Also, 62 nodes are found to be alive nodes after the end of 4000 iterations. Based on existence of alive nodes, it can be inferred that the proposed model is suited for lower energy consumption, and it also leads to an increase in the lifetime of the network.

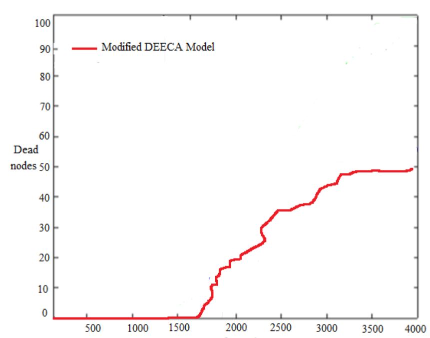

Fig 3. Dead Nodes versus No. of Iterations

The graph of live nodes using MDEECA model is shown in Figure 4. The model results in 62 live nodes and 38 dead nodes even after the completion of the defined iterations of 4000. Hence, the network lifetime increases as there are enough live nodes available for communication after these transitions.

The packets sent to the BS is plotted in Figure 5, and it is observed that the maximum number of packets sent to the base station for the iterations of 4000.

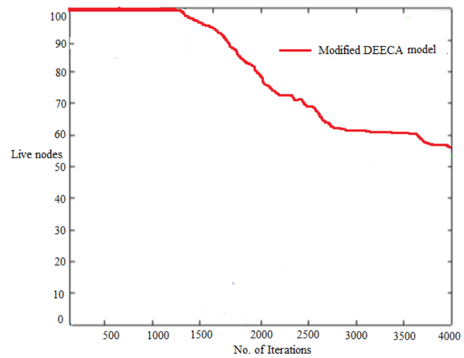

Fig 4. Live Nodes versus No. of Iterations

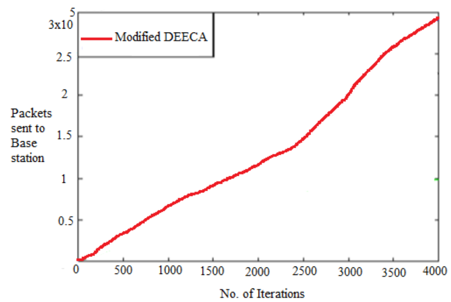

Fig 5. Packets sent to BS versus No. of Iterations

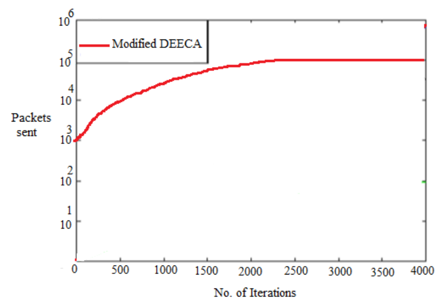

Fig 6. Packets sent versus No. of Iterations

The packets sent to the CH is shown in Figure 6. From which it is observed that the maximum number of packets sent to the cluster head for the iterations of 4000. Such a variation occurs because the proposed protocol adjusts the probability of a node becoming a CH and designs a reasonable cluster size.

The graph of number of CHs generated in each iteration is shown in Figure 7. It can be observed that the number of CHs generated is more for the proposed MDEECA model which in turn enhances energy efficiency. This is due to the proposed algorithm considering residual energy and distance to the sink node for evaluations.

The lifetime of the network, packets sent to the BS, and packets sent to the CH is tabulated in Table 3. It can be observed from the table that 9564 packets are sent to BS using the proposed model for first 1000 iterations. At the end of 4000 iterations, the model results in 29394 packets. In case of the packets sent to CH, 14456 packets are sent to CH for the first 1000 iterations, and 112464 packets are sent for 4000 iterations. Overall, in comparison to existing algorithms, the results obtained for the proposed MDEECA algorithm shows that MDEECA is more robust, it increases network lifetime, and decreases energy consumption.

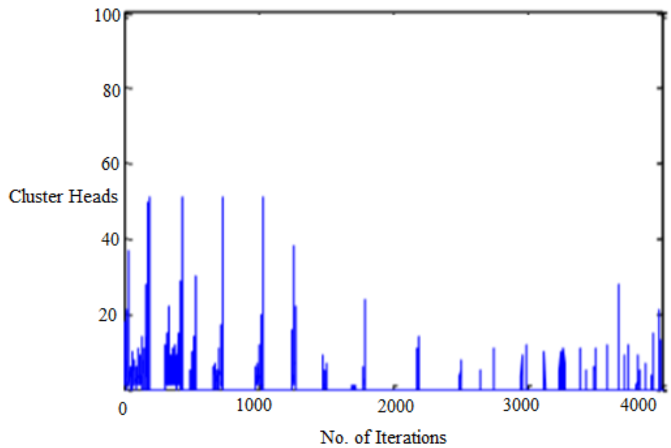

Fig 7. No. of Cluster Heads versus No. of Iterations

Table 3. Observationsand Comparisons of Lifetime, Packets sent to BS and CH versus No. of Iterations on DEEC and Proposed MDEEC algorithm.

Parameters	DEEC (Existing model) [11]	MDEEC (Proposed Model)
Lifetime of the Network	**No. of Iterations**	
	1384 (First node Die)	2432 (Half node Die) 3486 (Last node Die)
No. of packets sent to Base Station	**No. of Iterations**	**Packets sent**
	1000	9564
	2000	17400
	3000	24426
	4000	29394
No. of packets sent to Cluster Head	**No. of Iterations**	**Packets sent**
	1000	14456
	2000	82184
	3000	103454
	4000	112464

4 Conclusion

This article proposed the modified distributed energy efficient clustering (MDEECA) algorithm which extends the Distributed Energy-Efficient Clustering (DEEC) model by incorporating several parameters and modifications to enhance the cluster head selection process and increase network lifetime. The MDEECA algorithm introduces parameters such as scaling factor, selection of cluster head, threshold probability, and information related to neighborhood for the next cluster head selection. These parameters are applied to the DEEC model to optimize the process of choosing cluster heads and reduce the number of contenders for cluster head selection. From the obtained results, it is observed that the proposed MDEECA algorithm outperforms existing algorithms in terms of network lifetime. Specifically, during the first 1000 iterations, the proposed model successfully sends 9564 packets to the base station which is likely to be the central node in the network. Additionally, a higher number of packets (14456) are sent to cluster heads during the same period, indicating the effectiveness of the proposed MDEECA model in routing packets towards the appropriate cluster heads. Overall, the results suggest that the proposed MDEECA algorithm has the potential to be implemented in networks to extend the network lifetime due to its improved cluster head selection process and optimization of routing the packets within the network.

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