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# Energy-efficient and multi-stage clustering algorithm in wireless sensor networks using cellular learning automata

**Mohammad Ahmadinia**[1], **Mohammad Reza Meybodi**[2], **Mahdi Esnaashari**[2], **Hamid Alinejad-Rokny**[3],
[1] Department of Computer, Kerman Branch, Islamic Azad University, Kerman, Iran
[2] Department of Computer Engineering and Information Technology, Soft Computing Laboratory, Amirkabir University of Technology, Tehran, Iran
[3] School of Computer Science and Engineering, Faculty of Medicine, The University of New South Wales, Sydney, NSW, Australia

**Correspondence Address**:
Mohammad Ahmadinia
Department of Computer, Kerman Branch, Islamic Azad University, Kerman
Iran

## Abstract

One of the main challenges in wireless sensor networks is the energy constraints of sensor nodes which must be considered precisely when designing algorithms for such networks. Clustering is known as one of the approaches which can be used for addressing this challenge. In this paper, an efficient method for clustering wireless sensor networks by means of cellular learning automata has been presented (LaClustering). Proposed method selects cluster head (CHs) through several stages; each considers one parameter affecting the overall performance of the clustering. Parameters considered in different stages of the proposed algorithm are energy levels of the sensor nodes, number of neighbors of each node, network connectivity, and formation of balanced clusters. To evaluate the performance of the proposed method, several experiments have been conducted using the J-sim simulator and the proposed method has been compared with some of the best clustering algorithms reported in literature. The simulation results have shown that the proposed algorithm can provide clustering infrastructure with higher overall quality than the existing algorithms, especially in balancing the number of sensor nodes in different clusters and selecting CHs with higher energy levels.

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## Full Text

### 1. Introduction

Wireless sensor networks are used for monitoring and controlling particular phenomena in different environments. They consist of many inexpensive sensor nodes that are densely distributed in an environment. Data collected by sensor nodes must be transmitted to a central node, called the base station.

In direct transmission, each sensor node sends its data directly to the base station. This is not suitable for an energy-constraint network such as sensor networks. Thus, multi-hop transmissions are highly beneficial for such networks. One major problem with multi-hop communications is the excessive number of packets being exchanged between the neighboring nodes. This problem can be revealed by clustering the network.

Clustering is the act of dividing the network nodes into a number of independent groups, called the clusters. Each cluster has a node as a manager, called the cluster head (CH) which is responsible for collecting all the information produced within the cluster. CHs, then, send the collected information toward the base station either directly or through a multi-hop routing architecture consists of only CHs.

Clustering has some advantages such as (1) allowing for data aggregation in order to reduce energy consumption by sensors [1],[2] , (2) facilitating queries on the sensor network [3] , (3) forming an infrastructure for scalable routing [4] , and (4) providing a mechanism-efficient network-wide broadcast [5] . Clustering algorithms for sensor networks fall into two categories, centralized clustering and distributed clustering [6] . Centralized clustering protocols require the global network knowledge, introduce substantial storage, communication, and computation overheads and thus are not desirable for resource-constrained sensor nodes. Distributed clustering algorithms usually make decisions based on localized information [7],[8],[9] . In general, distributed clustering schemes introduce less communication cost when compared with centralized schemes.

In this paper, an efficient and distributed method for clustering wireless sensor networks by means of cellular learning automata (CLA) technique has been presented that we named it LaClustering.

In this method, clusters be formed and CHs be determined in three stages. In each stage, some of the CHs are determined. At the first stage, nodes with high number of neighbors are chosen as CHs. At the second stage, some of nodes are chosen as CHs using irregular cellular learning automata (ICLA) and at third stage, for covering common nodes that do not have any CH node in their neighborhood, some other CH nodes are chosen. Parameters considered in different stages of the LaClustering algorithm are energy levels of the sensor nodes, number of neighbors of each node, network connectivity, and formation of balanced clusters.

Rest of this paper is organized as follows. Section 2 presents a summary of the related work. Then, CLA as the main strategy for learning algorithm is presented briefly in Section 3. The proposed algorithm is described in Section 4. Simulation results are given in Section 5. Section 6 is the conclusion.

### 2. Related Work

In this section, we will briefly overview some of the existing clustering algorithms for wireless sensor networks.

Adaptive clustering hierarchy (LEACH) algorithm [1] . The operation of LEACH is separated into the following two phases: The setup phase and the steady state phase. During the setup phase, a predetermined fraction of nodes p, elect themselves as CHs by comparing a chosen random number with a predefined threshold. After the CHs have been elected, they broadcast an advertisement message to the rest of the nodes in the network that they are the new CHs. Upon receiving this advertisement, all the non-cluster head nodes decide on the cluster to which they want to belong, based on the signal strength of the advertisement. The non-cluster head nodes inform the appropriate CHs that they will be members of the cluster.

There are algorithms which elect CHs based on a certain criterion such as number of neighbor nodes [10],[11] , or remaining energy of the nodes [12] . In the algorithm presented in [13] , each node waits for a random duration. After this period, if no message is received from a certain CH, the node states itself as a new CH. In some other methods, such as the one in [14] , CHs are specified prior to network deployment. These specified nodes are placed in certain positions and other nodes are scattered around them. After the network deployment, these nodes try to form clusters having balanced traffic load. This means that fewer nodes are assigned to the clusters closer to the sink node and more nodes are assigned to the clusters far from the sink. In the sensor network considered in [15] , two classes of nodes are available; sensor nodes and aggregator nodes. Aggregator nodes are placed in certain position and play the role of CHs. In this paper, three different algorithms are presented for scattering sensor nodes around the aggregators. In [16] , sink node is assumed to be a mobile node which queries data from different part of the network based on its distance from different nodes. For this reason, it is required to have a dynamic clustering algorithm which can adapt itself to the changing position of the mobile sink, considering the overall energy consumption in the network. A number of different routing algorithms for sensor networks are surveyed in [17],[18] . One major class of these algorithms is the hierarchical routing. In hierarchical routing algorithms, at first a clustering scheme is applied to form a kind of hierarchy and afterward, the process of routing is divided into inter- and intra-cluster phases. In [19] , an algorithm called Hybrid Energy-Efficient Approach (HEED) has been given. This algorithm has the following four primary goals: (i) Prolonging network lifetime, (ii) terminating the clustering process within a constant number of iterations/steps, (iii) minimizing control overhead (to be linear in the number of nodes), and (iv) producing well-distributed CHs and compact clusters.

In [20] , an enhancement on HEED algorithm in which only nodes with residual energy higher than a specified threshold can become CH is presented. Also, at the end of the algorithm, when some nodes do not join to any cluster yet, unlike HEED in which all these nodes become CH, HEED algorithm is executed again for electing CHs among them.

In [21],[22] , methods are introduced for clustering nodes based on CLA that use the remaining energy of nodes and the number of neighbors for CH selection.

## 3. Cellular Learning Automata

In this section, we briefly review cellular automata (CA), learning automata (LA), CLA, and then introduce ICLA [22] .

Cellular Automata: CA are mathematical models for systems consisting of large number of simple identical components with local interactions. CA is a non-linear dynamical system in which space and time are discrete. The simple components act together to produce complicated patterns of behavior. The cells update their states synchronously on discrete steps according to a local rule. The new state of each cell depends on the previous states of a set of cells, including the cell itself, and constitutes its neighborhood.

Learning Automata: LA are adaptive decision-making devices that operate on unknown random environments. A learning Automaton has a finite set of actions to choose from and at each stage, its choice (action) depends upon its action probability vector. For each action chosen by the automaton, the environment gives a reinforcement signal with fixed unknown probability distribution. The automaton then updates its action probability vector depending upon the reinforcement signal at that stage, and evolves to some final desired behavior.

[INLINE:1]

for unfavorable ones. In these equations, a and b are reward and penalty parameters, respectively. For more information about LA, the reader may refer to [23], [24] .

Cellular Learning Automata: CLA, which is a combination of CA and LA, is a powerful mathematical model for many decentralized problems and phenomena. The basic idea of CLA, which is a subclass of stochastic CA, is to utilize LA to adjust the state transition probability of stochastic CA. A CLA is a CA in which a learning automaton is assigned to every cell. The learning automaton residing in a particular cell determines its action (state) on the basis of its action probability vector. Like CA, there is a rule that the CLA operates under. The local rule of CLA and the Actions selected by the neighboring LAs of any particular LA determine the reinforcement signal to the LA residing in a cell. The neighboring LAs of any particular LA constitute the local environment of that cell. CLA has found many applications such as image processing [25],[26] , rumor diffusion [27] , modeling of commerce networks [26] , channel assignment in cellular networks [28] , and VLSI placement [29] .

Irregular Cellular Learning Automata: An ICLA is a CLA in which the restriction of rectangular grid structure in traditional CLA is removed. This generalization is expected because there are applications such as wireless sensor networks, immune network systems, graph-related applications, etc., [22] that cannot be adequately modeled with rectangular grids. An ICLA is defined as an undirected graph in which each vertex represents a cell which is equipped with a learning automaton.

The learning automaton residing in a particular cell determines its state (action) on the basis of its action probability vector. Like CLA, there is a rule that the ICLA operate under. The rule of the CLA and the actions selected by the neighboring LAs of any particular LA determine the reinforcement signal to the LA residing in a cell.

## 4. Wireless Sensor Network clustering using cellular learning automata

In this section, we represent our clustering approach that uses CLA technique. To this end, we first give the assumptions about the network and the effective criteria used in designing the proposed algorithm and then present the proposed algorithm in details.

4.1 Assumptions and Criteria

Assume that all nodes in the sensor network are homogeneous, and each node of the network has the following two states: CH and common node (CN).

The node that is in the CH state is responsible for receiving information from other nodes in the network and sends them to the sink node. The amount of energy consumption in a CH node is higher than that of a CN. A CN collects produced data from its sensing region and sends them to its CH.

Two main criteria are considered in designing the proposed algorithm. These are as follows:

Energy consumption: The energy consumption in the network is analyzed from the following two aspects: The amount of energy consumed in each node: Nodes with higher energy level have greater chance to become CHs.Total energy consumption in the network: To decrease the total amount of energy consumption in the network, the clusters must be almost balanced in number of members and additionally, clusters should not be too crowded.Network connectivity: To support network connectivity, each CN in the network must be able to communicate directly with a CH.

4.2 The Proposed Method

The proposed clustering algorithm (LaClustering) consists of two phases: Clustering phase and steady state phase. In the clustering phase, which is performed when the network starts operating, all nodes of the network participate. During this phase, the role of each node which is initially set to unspecified is changed to either head or member using CLA technique. At the end of this phase, clusters are formed and each CN knows its CH. Then, the steady state phase will begin. In the steady state phase, CNs send the collected data to the CH, based on the schedules which have been determined by CHs and CHs send the collected data toward the sink. Moreover, in this phase, when energy level of a CH comes down from a determined threshold, the CH elects another node with more energy as CH. These phases of the algorithm are described below in detail:

4.2.1 Clustering Phase

As mentioned above, in this phase, clusters must be formed and CHs should be determined. Determining CHs is done in three stages. In each stage, some of the CHs are determined. The rest of this section describes these stages in details.

4.2.1.1 Stage 1

One of the most important parameters of clustering is the number of CH nodes. We want this number to be as few as possible. If the nodes with high number of neighbors are chosen as CHs, the total number of CHs will be reduced greatly. Thus, in the first stage of clustering, each node sends the number of its neighbors to its adjacent nodes. Then, the node that has the highest number of neighbors among its neighboring nodes chooses itself as the CH and informs its neighbors.

The nodes that are chosen as CH in this stage will not enter the next stages of clustering. Meanwhile, since the neighboring nodes of these nodes have at least one adjacent CH node, it is not necessary for them to enter the next stages as well. Hence, they choose themselves as CNs. Usually, at this stage, only a small number of nodes possess the condition to become head cluster. Therefore, a significant number of nodes are neither CH nor in the neighborhood of CH nodes and their situations are unspecified at this stage. Such nodes enter the next stages and their status will be determined using CLA.

[Figure 1] shows an example of the WSN after this stage. Large solid circles represent CH nodes and small solid circles represent member nodes, while the hollow circles represent unspecified nodes.{Figure 1}

4.2.1.2 Stage 2

At this stage, the status of nodes whose states are still unspecified will be determined using ICLA. For this purpose, an asynchronous ICLA which is isomorphic to the sensor network topology is created. Each unspecified node s i in the sensor network corresponds to the cell i in ICLA. Two cells i and j in ICLA are adjacent to each other if their corresponding nodes in the sensor network are close enough to hear each other's signals. The learning automaton in each cell i of ICLA, referred to as LA i , has two actions, CN and CH. Action CH is "declaring the node as a head" and action CN is "declaring the node as a member." The probability of selecting each of these actions is initially set to 0.5.

This stage is divided into a number of rounds. At the beginning of each round, the learning automaton of each node s i chooses one of its actions randomly, according to its action probability vector. Then, s i creates a packet containing the selected action, its energy level, and the number of its neighbors and broadcasts it in its vicinity. Next, s i waits to receive the selected actions of its neighboring nodes. According to the selected actions of s i and its neighbors, a reinforcement signal is generated. Following parameters are considered for generating the reinforcement signal:

Energy level of the nodes: A CH node is responsible for collecting data from cluster members and sending them to the base station. Therefore, the CH node will consume more energy than the cluster members. As a consequence, we prefer that nodes with higher residual energy to be elected as CHsThe number of node's neighbors: Since the energy consumptions of CHs are comparably high, it is rational to have a few number of such nodes. To this end, we prioritize nodes with higher number of neighbors for becoming CHsExistence of one CH in each locality: To ensure connectivity, each node must be either a CH or a neighbor of a CH. On the other hand, to prevent the number of CHs from becoming too large, no more than one CH should exist in each locality.

Generally, these parameters can be divided into two categories: Energy-related parameters that try to choose the nodes with more energy as CH and parameters related to the state and quality of clustering infrastructure that try to construct the appropriate number of clusters and form balanced clusters. In order to use these two sets of parameters in generating the reinforcement signal, we consider two coefficients (w e and w u), sum of which is equal to one (as it is indicated in equations (3) and (7)).

[INLINE:2]

Selection of action, generating reinforcement signal, and rewarding/penalizing the learning automaton of the node is repeated in each node asynchronously until one of the following conditions is met:

Probability of becoming CH becomes very close to either 0 or 1Number of rounds exceeds MAX_ITERATION

If the probability of becoming CH becomes very close to 1 (0), the node selects itself as a CH (CN); otherwise, the state of the node does not change (is unspecified).

4.2.1.3 Stage 3

In two previous stages, most of the CHs in the network have been identified. But it is possible that some of the nodes, which have been selected as CNs, do not have any CH node in their neighborhood. Thus, at this stage, for covering such nodes, some other CH nodes are added to CH nodes.

To this end the nodes that are CNs are not in the neighborhood of any CH node, and have the highest number of neighbor nodes than their neighbors become CHs and inform their situations to other neighboring nodes. Nodes whose states are common are not in the neighborhood of any CH node, but have a neighbor with more neighboring nodes, select that neighbor as CH and inform it by You_Cluster packet. This node changes its situation to CH and informs its neighbors. In this way, all the nodes which do not belong to any cluster become a member of a cluster.

4.2.1.4 Stage 4

After determining the status of the nodes in three previous stages, clusters must be formed. At this stage, CHs broadcast messages containing their location to their neighbors. Then, each CN elects the nearest neighbor CH as its CH. To create a cluster, each CN sends a JOIN_PACKET packet to its CH. CHs collect these packets, identify cluster members, and form clusters. Next, each CH creates a TDMA schedule for receiving data from its members and broadcasts it as a schedule packet (SCH_PACKET) to its cluster members.

4.2.2 Steady-state Phase

After the clustering phase is over, the steady state phase begins. In the steady state phase, CNs send their collected data to their CHs with determined periodic intervals and CHs send received data to the base station. Using the TDMA scheduling specified by the CH, each CN can determine the times at which it has to send its data to its CH. Thus, a CN can only switch on its transceiver during such times. This way, a CN can excessively save its battery.

The CHs are not active all the time, too. The cluster node becomes active only when it wants to receive data from a member node. If a cluster contains n common members, CH divides the round to n + 1 time intervals. CH at the beginning of each interval becomes inactive and at the end of the interval becomes active and receives data from a member node and then becomes inactive again. Thus, CH during a time period collects data from all member nodes and at the end of the period becomes active again and sends data to the base station node.

Although using this scheduling strategy saves the energy consumption of a CH to a great extent, the energy consumption of a CH is still more than that of a CN. Therefore, if no mechanism exists for changing the CHs, CH nodes die faster than the rest of the nodes. To prevent this from happening, we adapt a mechanism for changing the CH of each cluster. The mechanism works as follows: Whenever a CN sends its data to its CH, it additionally sends its residual energy level. At the end of each period, each CH computes the average energy level of its members and compares it with its energy level. If the energy level of a cluster is less than the average energy level of its members with a predefined threshold (THRESH_CHANGE), then that CH gives its role to a member with the highest energy level. This is done by sending a Get_Clustering packet to that member. In the next time period, each node that sends data to the CH receives a Change_Clustering packet from it and is informed about the new selected CH.

## 5. Simulation

In this section, performance of the proposed algorithm (LaClustering) is evaluated using a set of experiments. In these experiments, the results obtained from the LaClustering algorithm are compared with the results obtained from the LEACH [1] , the basic HEED [19] , its extension (Extended HEED) [20] , and novel algorithm presented in [22] (ICLA) that is based on LA.

In our experiments, nodes periodically report 526 bytes of data to the sink node. All simulations have been implemented using j-sim simulator. We use IEEE 802.11 as the MAC layer protocol. Nodes are placed randomly on a 2-dimensional area of size 100 (m) ×100 (m). In all experiments, and are set to 0.5, MAX_ITERATION is set to 50, a and b are set to 0.1, R c is set to 20 (m), THRESH_CHANGE (Threshold for changing CH) is set to 0.2, and initial energy level of the nodes is selected uniformly and randomly from the range [1.8, 2.0] (J). First order radio model specified in [15] is used for estimating the amount of energy consumed for packet transmissions. All packets except for data packets, which are 526 bytes long, are assumed to be 8 bytes. Simulations are performed for 50, 100, 200, 300, 400, and 500 nodes. The results are averaged over 40 runs.

In these experiments, we study the quality of the proposed clustering algorithm in terms of Number of clusters in the clustering infrastructure produced at the end of the clustering, Percentage of the sparse clusters which is defined as the percentage of clusters having only one head and one member, Ratio of the mean energy level of heads to the mean energy level of members, network lifetime, and variation coefficient in size of clusters defined through equation (10) given below.

[INLINE:3]

In the above equation, $\sigma cs$ is the standard deviation of the clusters sizes and $\mu cs$ is the average size of the clusters. $\kappa$ is a notion of balancing level of the clustering infrastructure in terms of the number of members of each cluster. A smaller $\kappa$ indicates a more balanced clustering infrastructure.

Experiment 1

In this experiment, we compare the quality of the clustering infrastructure produced using the LaClustering, LEACH, HEED, ExtendedHEED, and ICLA with respect to (1) number of clusters, (2) percentage of sparse clusters, (3) variation coefficient in size of clusters ($\kappa$), and (4) ratio of the mean energy level of the heads.

[Figure 2] compares the number of generated clusters in the proposed method with the existing methods. As it is shown, the number of clusters in the infrastructure resulted from the LaClustering algorithm is less than the other methods and almost equal to that of ICLA method.{Figure 2}

[Figure 3] and [Figure 4] compare the LaClustering algorithm with the other algorithms in terms of the percentage of the sparse clusters and the ratio of the mean energy level of heads, respectively. These figures show that the clustering infrastructure formed by the proposed method is better than the other four methods in terms of the two mentioned parameters.{Figure 3}{Figure 4}

[Figure 5] compares the proposed algorithm with the other three algorithms in terms of the variation coefficient in size of clusters (k). This figure shows that the variation coefficient in size of clusters in LaClustering algorithm is lower than of the other algorithms. This indicates that the proposed algorithm is better than other algorithm in balancing the number of sensor nodes in different clusters.{Figure 5}

Experiment 2

The network operation continues until the time at which a node in the network dies. In other words, network lifetime is defined to be the time elapsed from the network startup to the time at which a node in the network dies [13] .

This experiment whose result is given in [Figure 6] compares the network lifetime for the proposed algorithm with that of LEACH, HEED, ExtendedHEED, and ICLA algorithms. [Figure 6] shows that the network lifetime for the proposed algorithm is significantly higher than that of the other algorithms.{Figure 6}

## 6. Conclusion

In this paper, we proposed a new clustering algorithm for sensor networks based on CLA technique. To evaluate the performance of the proposed method, several experiments were conducted and the results obtained from the proposed algorithm were compared with that of LEACH, basic HEED, ExtendedHEED, and ICLA-based in terms of the following criteria: Number of clusters in the clustering infrastructure produced at the end of the clustering, percentage of the sparse clusters, cluster size variation coefficient, ratio of the mean energy level of the heads to the mean energy level of the members, and network lifetime. Experiments showed that the proposed clustering algorithm substantially outperforms the existing clustering algorithms in terms of the above mentioned criteria and as a result, can better prolong the network lifetime.

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