Musicians'-Inspired Clustering Protocol for Efficient Energy Wireless Sensor Networks

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Abstract—In the development of cluster-based energy-efficiency protocols for Wireless Sensor Networks (WSNs), a particularly challenging problem is how to dynamically organize the sensors into a wireless communication network and route sensed information from the field sensors to a remote base station in a matter that prolongs the lifetime of WSNs. This paper presents a new energy-efficient dynamic clustering algorithm for WSNs that automatically organizes the sensors into an appropriate number of clusters in the network. This algorithm, which is based on a Harmony Search Algorithm, music based meta-heuristic optimization algorithm, eliminates the need to set the number of clusters a priori. In addition, a multi-objective approach is utilized in the cluster head selection algorithm in order to select the best set of cluster heads. Simulation results demonstrate that the proposed algorithm can achieve an optimal number of clusters, as well as prolong the network lifetime and increase the data delivery at the base station when compared to other well-known clustering-based routing protocols.

Keywords- Wireless Sensor Networks; Energy Efficient Routing Protocols; Harmony Search Algorithm; Fuzzy Clustering.

I. INTRODUCTION

Wireless sensor networks are a brilliant technology that have potential applications in both civilian and military domains, including environmental monitoring, surveillance, healthcare, intelligent building control, traffic control, object tracking, etc. [1]. WSNs consist of a large number of autonomous sensor nodes equipped with sensing capabilities, wireless communication interfaces, limited processing and energy resources. One or more powerful base stations (BSs) serve as the final destination of the data. WSNs are used for distributed and cooperative sensing of physical phenomena and events of interests [2].

In this infrastructure, the energy consumption of each node that is used to pass the sensory data to the final destination is considered a main concern for designing WSNs routing protocols, since the economical usage of sensor nodes in WSNs will enormously affect the operational lifetime of WSNs. This is based on the fact that the sensor nodes are equipped with limited energy sources (lightweight battery) and the replacement of these batteries maybe inapplicable or impossible [3]. Thus, the optimum exploitation of this energy would prolong the use and efficiency in the performance of WSNs. Therefore, design routing algorithms that can consume less energy, while maintaining the efficiency and robustness of WSNs is desirable.

In the light of this fact, a lot of cluster-based routing protocols to address energy-efficiency in data collection applications were proposed such as LEACH and LEACH_C algorithms [4,5] and others as in [6,7]. In such techniques, all sensors are organized into clusters. Each elected cluster head (CH) acquires data from sensors within its own cluster, performs data aggregation, and transmits fused data directly to the BS, which allows most nodes to transmit in small distances and to reduce the amount of data sent in the network to save battery energy.

However, most proposed algorithms in this domain do not cover the determination of how many clusters that will be optimal for the given WSN. In most of these algorithms, the number of clusters has to be given by the network designer before the cluster process begins [8]. It is certainly one of the key parameters that determines the lifetime of the WSNs. This is based on the fact that if there are fewer clusters, non-CH nodes are probably to consume too much energy transmitting sensory data to their CHs because most of the clusters will be of a large size. Contrariwise, if there are too many clusters, the energy consumed by non-CH nodes to transmit data to their cluster head decreases. At the same time, the probability of consuming much more energy by CHs are increased where CHs are required to fuse the sensory data and transmit them over a large distance to the BS [8]. Therefore, in order to minimize the energy consumption and prolong the lifetime of WSNs, the clustering scheme must be able to find the optimal number of clusters before the clustering process begins.

To create an efficient and energy-aware routing protocol in WSNs while avoiding above mentioned weaknesses, we seek mechanisms from similar problems in nature and adapt them to suit the challenges of WSNs. Harmony Search Algorithm (HS) is a relatively new meta-heuristic algorithm developed by Geem et. al. [9] to solve optimization problems. Ever since the emergence of this algorithm, it has been able to attract many researchers to develop HS-based applications in many optimization problems [10]. In HS, a candidate solution of an optimization problem corresponds to a musical harmony composed of notes played by a group of musicians. Each decision variable in a candidate solution is analogous to a musician with its value range analogized by the pitch range within which the corresponding musician plays the note.

This paper proposes a Dynamic Clustering algorithm using HS algorithm for Wireless Sensor Networks (DCHS_WSN) which automatically decides the number of clusters that can
result in minimum total network energy dissipation. The proposed clustering protocol is a de-centralized clustering algorithm where the base station determines the optimal number of clusters and do allocate sensor nodes into these clusters. Later on, the selection process of each CH in each iteration is done locally in each cluster during the network lifetime. In other words, the infrastructure of the network is permanent once it designed and no node can be moved from one cluster to another. In DCHS-WSN, the PBMF cluster validity index [11] is used as a fitness function to validate the CHs selection process obtained from each harmony memory vector. The PBMF index measures if the new solution vector can increase the inter-cluster distances between clusters (separation) and decreases the intra-cluster distances within each cluster (compactness) that in turn will lead to find the optimal number of cluster and build the most appropriate network infrastructure. In addition to that, we propose a new fitness function that will be used, after network infrastructure is built, in the selection process of CHs in each iteration of network lifetime. The residual energy, the location of each candidate node within a cluster and the location of each candidate node regarding the BS are the main factors of the proposed fitness function.

The paper is arranged in following sections. Section II provides the preliminaries of the network and radio model explored. A detailed description of the proposed protocol using Harmony Search algorithm is given in Section III. The simulation study of the proposed protocol is presented in section IV. We conclude our findings in Section V.

II. PRELIMINARIES

This section presents the assumptions and radio model of the network under consideration.

A. Assumption

- The base station is located far from the sensor nodes and is immobile.
- All nodes in the network are homogeneous and energy constrained.
- Symmetric propagation channel.
- Nodes have location information with respective energy levels.
- Nodes have no mobility.

B. Radio Energy Models

The in the radio energy model used in this work, the transmitter dissipates energy to run the radio electronics and the power amplifier, and the receiver dissipates energy to run the radio electronics. The energy consumption for transmitting a b bit message over a distance d is:

\[ E_{Tx} = E_{elec} \times b + E_{fa} \times b \times d^2, \quad d < d_0 \]  
\[ E_{Rx} = E_{elec} \times b + E_{mp} \times b \times d^4, \quad d \geq d_0 \]  

And for receiving this message respectively is:

\[ E_{Rx} = E_{elec} \times b \]

Where \( E_{elec} \) is the energy spent to operate the transceiver circuit, \( E_{fa} \) and \( E_{mp} \) are the energy expenditure of transmitting one bit data to achieve an acceptable bit error rate and this depends on the distance of transmission in the case of free space model and multipath fading model [4]. If the transmission distance is less than a threshold \( d_0 \), the free space model is applied; otherwise, we use the multipath model. The threshold \( d_0 \) is calculated as:

\[ d_0 = \sqrt{\frac{E_{fs}}{E_{mp}}} \]  

Another parameter is also taken into consideration is the data aggregation which is performed by the cluster head to reduce the total amount of data sent. In this simulation, we assume that the overall data collected by a cluster of \( n \) nodes, where each node collects \( b \) bits of data, can be compressed to \( b \) bits regardless of the number of nodes in that cluster. Based on that, the data aggregation energy expenditure is set as \( E_{da} = 5nJ/bit/message \).

III. THE PROPOSED PROTOCOL

In this section, we present the proposed clustering protocol for the energy efficient problem in WSN. The proposed protocol is a decentralized clustering protocol where base station establishes the infrastructure of given WSN. The base station predicts the optimal number of clusters that may WSN possess and allocates sensor nodes into clusters according to the information of their location since all nodes have the same energy level in this stage (homogenous WSN as assumed earlier). To reach this target, we proposed a Dynamic Clustering approach using HS algorithm named (DCHS-WSN) that automatically decides the number of clusters and can result in minimum total network energy dissipation. More details are described in the following Setting phase. Later on, the selection process of each CH in each iteration is done locally in each cluster during the network lifetime. In other words, the infrastructure of the network is permanent once it designed and no node can be moved from one cluster to another. More details are described in the flowing CH-Election phase. In the data transmission phase and once the CH is elected, the cluster heads collect data from all cluster members and transfer to the BS. The description of these three phases is presented in the following sections.

Phase 1: Setting Phase

The setting phase is the phase of building the infrastructure of the WSN where the optimal number of clusters as well as the locations of cluster heads is explored. Given a WSN consists of \( N \) nodes randomly distributed over an area of \( M \times M \) meters. The base station is permanently located at \( X \) meter. Based on the geographical location of each node, the base station automatically determines the appropriate number of clusters as well as the locations of cluster heads and then do allocate sensor nodes into these clusters. This WSN architecture is permanent during the live time of the network where each node cannot move from one cluster to another,
while the CH election process for the upcoming rounds (stages) will be done independently in each round for each cluster as described in CH-Election phase. To reach this goal, we propose a DCHS-WSN to automatically determine the optimum number of clusters and simultaneously allocate sensor nodes into these clusters with minimal user interface. The proposed algorithm is guided by some ideas from the algorithm introduced in [12, 13], however, the work in [12, 13] is oriented to solve the problem of image segmentation, while the algorithm in this work is only concerned with the application in a WSN area. The following is a description of DCHS-WSN algorithm.

**DCHS-WSN Algorithm**

This section describes how DCHS-WSN is designed and applied to optimally cluster the WSNs during the setting phase. This algorithm is based on HS to find the optimal number of clusters as well as the locations of cluster heads. HS as mentioned earlier mimics the improvisation process of musicians' with an intelligent way. The analogy between improvisation and optimization is likely as follows [10]:

- Each musician corresponds to each decision variable.
- Musical instrument’s pitch range corresponds to the decision variable’s value range.
- Musical harmony at a certain time corresponds to the solution vector at certain iteration.
- Audience’s aesthetics corresponds to the objective function.

Just like musical harmony is improved time after time, solution vector is improved iteration by iteration. In general, the DCHS-WSN has five steps as in HS and they are described as follows:

**Step 1. Initialize the DCHS-WSN Parameters**

The parameters of the DCHS-WSN are:

- Harmony Memory Size (HMS);
- Harmony Memory Considering Rate (HMCR), where HMCR ∈ [0, 1];
- Pitch Adjusting Rate (PAR), where PAR ∈ [0, 1];
- Stopping Criteria (i.e., number of improvisation (NI));

**Step 2. Initialization of Harmony Memory (HM)**

Each harmony memory vector encodes the CHs of the given WSN. However, since the number of these CHs is unknown for the given WSN, a possible range of number of clusters that the given WSN may possess is tested. Consequently, each harmony memory vector can vary in length according to the randomly generated number of clusters for each vector. To initialize the HM with feasible solutions, which is the index of a sensor node that refer to the actual node location, each harmony memory vector initially encodes a number of CHs, denoted by 'CHNo', such that:

\[ CHno = (\text{rand} \times (\text{CHMaxNo} - \text{CHMinNo})) + \text{CHMinNo} \]  

Where \( \text{rand} \) is a function that generates a random number \( \in [0,1] \), and CHMaxNo is an estimate of the maximum number of clusters (upper bound), CHMinNo is the minimum number of clusters (lower bound). In this simulation, the value of the upper bound is set to \( \sqrt{\text{NS}} \), \( N \) is the number of nodes in the given network, as recommended by authors in [11], while the value of the lower bound is set to 2. Therefore, the number of clusters CHno will range from CHMinNo to CHMaxNo. Even though the vector length is allowed to vary, for a matrix representation, each vector length in HM must be made equal to the maximum number of clusters (CHMaxNo). As a result, the remnants of unused vector elements (referred to as “unused”) are represented with ‘S’ sign. It is worth mentioning here, that the fitness function for each harmony vector is calculated and saved in harmony memory as explained in 'Evaluation of Solutions' Section.

**Step 3. Improvise a New Harmony**

The new harmony vector is a vector with the candidate CHs, and the values of this vector is generated depending on the HS’s improvisation rules. This new harmony vector inherits the values of its components \( a^{\text{NEW}} \) from the harmony memory vectors stored in HM with the probability of HMCR, otherwise, the value of the components of the new harmony vector is selected from the possible range R (indices of nodes) with a probability of (1-HMCR) as follows:

\[ a^{\text{NEW}} \left\{ \begin{array}{ll} a^{\text{NEW}} & \in \{a^1, a^2, a^3, \ldots, a^{\text{HMS}}\} \\ a^{\text{NEW}} & \in R \\ w.p \text{HMCR} \\
 w.p (1 - \text{HMCR}) \end{array} \]  

Furthermore, the new vector components which are selected out of memory consideration operator are examined to be pitch adjusted with the probability of PAR as follows:

\[ a^{\text{NEW}} \left\{ \begin{array}{ll} \text{Adjusting Pitch} & \in \{a^{\text{NEW}}\} \\ \text{No change} & \in \{a^{\text{NEW}}\} \\ w.p \text{PAR} \\
 w.p (1 - \text{PAR}) \end{array} \]  

If a generated random number rand \( \in [0,1] \), within the probability of PAR then, the new candidate CH (a\(^{\text{NEW}}\)) will be adjusted to the nearest node based on the minimum Euclidian distance between the candidate CH under consideration and other nodes in the same cluster. The other important issue worth mentioning is that when the inherited components of the new harmony vector have unused values (‘S’). In this case, no pitch adjustment will take place. Once the new harmony vector is generated, a count is done on the generated number of CHs in the new vector. If it is less than the minimum number of CHs ‘CHMinNo’, the new vector will be rejected. Otherwise, the new vector will be accepted and a fitness function is computed using a cluster validity measurement described in the following Section.

**Evaluation of Solutions**

The evaluation of each harmony memory vector indicates the degree of goodness of the solution it represents. In order to evaluate the goodness of each harmony memory vector, the unused elements (‘S’) that may appear in the harmony vector is removed and the remaining components which represent the CHs are used to cluster the given WSN. In this paper we used the fuzzy technique in clustering process where the sensor node
is assigned to one or more clusters with a membership grade. The fuzzy membership value for each node is calculated as in [14] as follows:

\[ u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \frac{||n_i - CH_k||}{||n_i - CH_k||} \right)^{m-1}} \]  

(8)

Where \([\alpha_k]_c\) are the CHs of the clusters \(c\) and \(||.||\) denotes an inner-product norm (e.g., Euclidean distance) from the node \(n_i\) to the \(j^{th}\) CH, and the parameter \(m \in [1, \infty)\) is a weighting exponent on each fuzzy membership that determines the amount of fuzziness of the resulting classification. After that, the goodness of the clustering result is measured using a cluster validity index. Therefore, the validity index measurement is used as the fitness function in this study. Actually what is need is to test whether the new solution vector can improve the clustering result or not and this can be measured by calculating the inter-cluster distances (separation) between clusters and the intra-cluster distances (compactness) within the cluster members. In this case, the target is to maximize the separation measurement and minimize the compactness measurement. Several indices for the fuzzy clustering assessment have been proposed (e.g., see [15], [16] and references therein). In this paper, we used PBMF-index [11], which is defined as follows:

\[ PBMF(c) = \frac{1}{c} \left( \frac{E_c}{E_c} \times D_c \right)^p \]  

(9)

Where \(c\) is the number of clusters. Here

\[ E_c = \sum_{j=1}^{c} \sum_{i=1}^{n} u_{ij} ||n_i - CH_j|| \]  

(10)

And

\[ D_c = \max_{i \neq j} ||CH_i - CH_j|| \]  

(11)

Where \(CH_i\) is the center of the \(i^{th}\) cluster, the power \(p\) is used to control the contrast between the different cluster configurations and it is set to be 2. \(E_i\) is a constant term for a particular WSN and it is used to avoid the index value to be closed to zero; it is set to be 10000. The value of \(m\), which is the fuzziness weighting exponent, is experimentally set to (1.5). \(D_c\) measures the maximum separation between two clusters over all possible pairs of clusters. \(E_c\) measures the sum of \(c\) within-cluster distances (compactness). The maximum value of PBMF-index indicates correct clustering results and therefore the correct number of CHs that could be gained. Consequently, maximization of the fitness function is desirable to reach the near-optimal solution.

**Step 4. Update the Harmony Memory**

Then, the new vector is compared with the worst HM solution in terms of the fitness function. If it is better, the new vector is included in the HM and the worst harmony is excluded.

**Step 5. Check the Stopping Criterion**

This process (steps 3 and 4) is repeated until the maximum number of iterations (NI) is reached. In the end, the best solution among the maximum value of fitness function of each HM solution vectors is selected to be the best solution vector.

**Phase 2: CH-Election Phase**

After the infrastructure of the WSN is developed by DCHS-WSN in the base station, the CHs election process for the upcoming rounds is done locally in each cluster. Each CH (the one that is elected from the previous round) will calculate the average energy level of all alive nodes in that cluster. Only the nodes which have residual energy higher than the average level are qualified to be a CH candidate, \(cd_i \in CD_c\). The competition between candidate nodes to be a CH is based on the following factors:

- The residual energy,
- The location of each candidate node within a cluster.
- The location of each candidate node regarding the BS.

These factors are the main components of our proposed objective function that is used to election process for CHs. The proposed objective function is described as follows.

\[ CH_{obj} = \max_{\forall cd_i \in CD_c} \left\{ \frac{E_{cd_i} \times q}{\alpha \times f_1 + (1 - \alpha) \times f_2} \right\} \]  

(12)

Where

\[ f_1 = \sum_{i=1}^{n} ||node_i - cd_i|| \]  

(13)

\[ f_2 = ||cd_i - BS|| \]  

(14)

In this objective function, \(E_{cd_i}\) is the residual energy of the candidate cluster head \(cd_i \in cluster\ C_j\). \(q\) is a constant term for a particular WSN and it is used to avoid the objective function value from approaching zero and it is set as \(q = 1000\). \(f_1\) is the Euclidean distance of nodes, \(node_i \in cluster\ C_j\) to their candidate cluster head \(cd_i\), while \(f_2\) is the Euclidean distance of the candidate cluster head \(cd_i\) to base station. The constant \(\alpha\) is the influence of \(f_1\) and \(f_2\) in the objective function. This objective function tends to minimize the intra-cluster distance (compactness) between sensor nodes and their cluster head, which in turn minimize the energy expenditure, required to passing the sensed data from each node to their CH. Furthermore, this objective function is also tends to minimize the distance between CH and the base station BS which in turn minimize the energy expenditure required to passing the aggregated date from each CH to their BS. Therefore, finding the maximum value of the objective function \(CH_{obj}\) in each round of the proposed protocol for each cluster \(C_j\) is desired and indicates that the candidate cluster head \(cd_i\) is the best among other candidate competitors. After the optimal CHs are found, each cluster head transmits its information to the nodes that belong to its cluster.
Phase 3: Data Transmission Phase

Once a CH is elected, each node within a cluster receives a message telling about the new CH. The sensor nodes start turn on their radio component for a very short period of time to perform sensing and transmit data to the CHs. CHs in their turn aggregate and send the sensed data to the BS, thus the amount of information transmission is reduced that result in the reduction of energy consumption. Both CH-Election phase and data transmission phase are repeated in each round of the proposed protocol.

IV. SIMULATION RESULTS

To evaluate the proposed protocol, a simulating of a 100 nodes network using MATLAB is developed. These sensor nodes cover an area of 100m x 100m and randomly deployed (however, no two nodes can be in the same location). This means that the horizontal and vertical coordinates of each sensor are randomly selected between 0 and the maximum value of the dimension (e.g. 100). Each node has initially 1 Joule of energy. The base station is located at the position (50,175). The coefficient $\alpha$ in (12) is set as $\alpha = 0.75$, this is to give the compactness factor more influence than the location of the candidate cluster head $c_d$, regarding the BS. The radio energy parameters used in our simulations are set as: $E_{\text{elec}} = 50\text{pJ/bit}$, $E_{\text{fs}} = 10\text{ pJ/bit/m}^2$ and $E_{\text{imp}} = 0.0013\text{pJ/bit/m}^4$ [4]. The size of the message that nodes send to their cluster heads as well as the size of the message that a cluster head sends to the BS is set to $b=4000$ bits/message. While DCHS-WSN parameters are experimentally set as: HMCR=0.95, PAR=0.30, HMS=30 and NI=30000.

The simulations have two parts and are conducted to verify the proposed dynamic clustering algorithm DCHS-WSN and the performance of the proposed routing protocol in term of WSN lifetime, respectively.

A. Simulations on Dynamic Clustering DCHS-WSN

In this part, the proposed DCHS-WSN algorithm is evaluated. Since HS algorithm is heuristic in nature, so, we performed 30 trials with several random network topologies to obtain the best solution. Fig. 1 shows how a 100 nodes network is randomly deployed and the location of their base station. Fig. 2 shows how DCHS-WSN can cluster the given network and build their infrastructure. Fig. 3 shows the plot of number of clusters obtained by DCHS-WSN algorithm in each trail. It can be seen that the number of clusters obtained by DCHS-WSN algorithm varies between 3 to 5 which is the optimal range as mentioned in [5]. The plot confirms that the proposed algorithm can achieve the optimal number of clusters that leads to greater energy saving in the network.

B. Simulations on Clustering-based Routing Protocol

After the optimal number of clusters is obtained by DCHS-WSN algorithm, a demonstration of the system lifetime, defined by the number of nodes remains alive over time for the simulation in the network area, is considered. A comparison of our proposed protocol with well-known clustering-based routing protocols is conducted. These protocols are: Low Energy Adaptive Clustering Hierarchy (LEACH) [4], Distributed multilevel clustering algorithm for heterogeneous wireless sensor networks, (DEEC) [16], Threshold sensitive Energy Efficient sensor Network protocol (TEEN) [17], Stable Election Protocol (SEP) [18] and hierarchical cluster-based routing protocol (HCR) [19]. Table I shows these protocols compared with our proposed protocol in term of the duration of time up to the first dead node. It can be observed that the network lifetime for our proposed protocol increases significantly compared to DEEC, HCR, SEP, LEACH and TEEN. This improvement is based on different factors. Firstly, significant energy saving is achieved by DCHS-WSN.
algorithm through the use of dynamic clustering where the optimal number of cluster is chosen and each node joined the most appropriate cluster. This is based on the strength of the harmony search algorithm to explore the search space (sensor nodes) and find out the most appropriate network infrastructure. Furthermore, the objective function that is used in DCHS-WSN is oriented to minimize the distance from non-cluster head nodes to cluster head and the distance from cluster head to the base station. Secondly, the de-centralized technique proposed in our protocol leads to lower network energy expenditure. This is based on the reduction of the energy expenditure required to send control messages from alive nodes to their cluster head, where the process of selection of a new CH is done, instead of the base station telling about their residual energy. Thirdly, the multi-objective function adopted in our proposed protocol attempts to produce a set of good compromises or trade-offs where the values of all the objective functions are acceptable to the system requirements. As a result, this protocol can obtain an optimal set of cluster heads that are evenly distributed across the network with optimal network configuration, which further reduces the total network energy dissipation.

### Table I. Duration of Time Up to the First Node Dies in WSN.

<table>
<thead>
<tr>
<th>Protocols</th>
<th>Lifetime of the First Dead Node (Rounds)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LEACH</td>
<td>1284</td>
</tr>
<tr>
<td>DEEC</td>
<td>353</td>
</tr>
<tr>
<td>TEEN</td>
<td>1759</td>
</tr>
<tr>
<td>SEP</td>
<td>1300</td>
</tr>
<tr>
<td>HCR</td>
<td>457</td>
</tr>
<tr>
<td>OUR PROTOCOL</td>
<td>1875</td>
</tr>
</tbody>
</table>

### V. Conclusion

In this paper, a dynamic clustering algorithm for WSNs using a harmony search algorithm is proposed. The use of dynamic clustering eliminates the requirement of determining the number of clusters in the simulation a priori. Furthermore, a de-centralized cluster-based protocol is proposed where the selection process of cluster heads in each simulation round is conducted in each cluster instead of the base station. This is based on a new a multi-objective function where the network energy consumption, intra-cluster distance and cluster to base station distance are its main factors. Simulation results have shown that the proposed algorithm can achieve an optimal number of clusters in each round during simulation. Moreover, the proposed protocol also offers improvement in network lifetime compared to algorithms such as LEACH, SEP, TEEN, HCR and DEEC.

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### References


