

Minimizing Energy Consumption and Collision by using Cluster-based Energy-efficient Scheme in Wireless Sensor Networks

Karthika K.P.R.C

PG Scholar

Sri Ramakrishna Engineering College

Coimbatore

Karthikacs20@gmail.com

Mr.T.M.Thiyagu

Assistant Professor

Sri Ramakrishna Engineering College

Coimbatore

t.m.thiyagu@gmail.com

Abstract

A wireless sensor network (WSN) consists of spatially distributed autonomous sensors to monitor physical or environmental conditions and to cooperatively pass their data through the network to a main location. In the sensor network (WSN), the connected dominating set (CDS) concept has recently emerged as a promising approach to the area coverage but there is more energy consumption. So, to make a good trade-off between the network connectivity, coverage, and lifetime, a proper number of sensors must be activated. We use a technique called a degree-constrained minimum-weight extension of the CDS problem called DCDS to model the area coverage in WSNs[1]. The proper choice of the degree-constraint of DCDS balances the network load on the active sensors and significantly improves the network coverage and lifetime. A learning automata-based heuristic named as LAEEC is proposed for finding a near optimal solution to the proxy equivalent DCDS problem in WSN. The computational complexity of the proposed algorithm to find an $\frac{1}{1-\epsilon}$ optimal solution of the area coverage problem is approximated. By using this

method, achieves control message overhead, percentage of covered area, residual energy, number of active nodes (CDS size), and network lifetime. But in this method there is communication collisions and redundant messages in the wireless sensor network. So, in order to overcome this problem, we introduce a cluster-based efficient-energy coverage scheme called CSA_VS (Cluster-based Scheduling Algorithm–Virtual Sensor) to ensure the full coverage of a monitored area while saving energy. CSA_VS uses a novel sensor-scheduling scheme based on the k-density and the remaining energy of each sensor to determine the state of all the deployed sensors to be either active or sleep as well as the state durations. So that provides better performance in terms of the number and the percentage of active sensors to guarantee the area coverage. So, by using this method we achieve efficient network coverage with less energy consumption and avoid communication collisions and redundant messages in a sensor network.

Keywords: lifetime, covered area, coverage extension, overhead, energy consumption.

INTRODUCTION

1. Introduction to wireless network

Wireless network refers to any type of computer network that utilizes some form of wireless network connection. Wireless telecommunication networks are generally implemented and administered using radio communication. This implementation takes place at the physical level of the OSI model network structure. An access point AP connects wireless clients to the wired LAN. Client devices on a network do not typically communicate directly with each other communicate via an access point. In essence, an access point converts the data packets from the 802.11 frame encapsulation format in the air to the 802.3 Ethernet frame format on the wired Ethernet network. Wireless networks provide an inexpensive and easy way to share a single Internet connection among several computers. This means you only need one modem, and you can add additional computers to the network just by plugging in a wireless card and turning them on. The new machines are connected to the Internet immediately. A wireless network also lets you access files and printers from anywhere in your home. It allows you to synchronize files you have on your laptop with your home computer, and you can easily send files between computers as well. Using a wireless network to transfer files is faster than sending them via e-mail or burning them to a CD. Because printers connected to one of the computers on a network are shared by all the computers on that network, you can write documents anywhere in your home, press the 'print' button, and collect the

printed files from a printer that is connected to another computer.

2. Existing System

In the existing system, we introduce a technique called the degree-constrained minimum weight version of the CDS, so called DCDS, is presented to alleviate the above mentioned problems with the CDS based area coverage protocols. DCDS is the CDS having the minimum weight subject to a predefined degree-constraint. The weight associated with each node is defined as the inverse of its residual energy. Therefore, the DCDS maximizes the network lifetime by selection of the sensors with the maximum residual energy. A DCDS is a CDS in which no node has a degree greater than a predefined degree-constraint. Therefore, by the proper choice of the degree-constraint the DCDS is able to make a trade-off between the percentage of the covered area and the network lifetime[2]. This paper proposes a learning automata based heuristic called LAEEC (short for learning automata based energy-efficient coverage protocol)[3] to construct the DCDS in the WSNs. The computational complexity of the proposed algorithm to find a $\frac{1}{1-\epsilon}$ optimal solution of the area coverage problem [2] is approximated. The Extensive simulation experiments are performed to show the performance of the proposed area coverage algorithm. The obtained results show the superiority of the proposed algorithm over the best existing methods in terms of the control message overhead, percentage of covered area, residual energy, number of active nodes (CDS size), and network lifetime.

3. Proposed System

In the proposed system, introduce a new technique called a cluster-based energy-efficient coverage algorithm [4] called CSA_VS (Cluster-based Scheduling Algorithm –Virtual Sensor) to deal with the problem of preservation coverage and the problem of saving energy. Sensors are assumed that they have limited battery energy. Sensing, transmitting and receiving activities consume battery energy of a sensor, and thus limit the network lifetime. In this work, we determine the statute of all the deployed sensors to be either active or sleep based on their capabilities as well as the state durations, such that the network lifetime is maximized. We used clustering approach because it permits to save energy by avoiding frequent communication collisions and redundant messages in a sensor network since only the cluster-heads that are responsible for transmitting the collected data to the remote sink, directly or via multi-hop transmission mode. Moreover, CSA_VS determines whether every point on the monitored area of a wireless sensor network is covered by k ($k \geq 1$) sensors or not. CSA_VS is performed as follows: First, it schedules sensor activities to maintain the full area coverage based on the algorithm. Then, it evaluates the coverage ratio of the area using virtual sensor approach. If this coverage ratio is lower than the ratio required, CSA_VS would improve it while activating other sensors. Moreover, when the coverage ratio is less than 100% then there are holes in the monitored area i.e. points not covered in the monitored area. The emergence of these holes may be due to the failure

of sensors or there exist sensors in sleeping mode in these regions.

4. Architecture Diagram

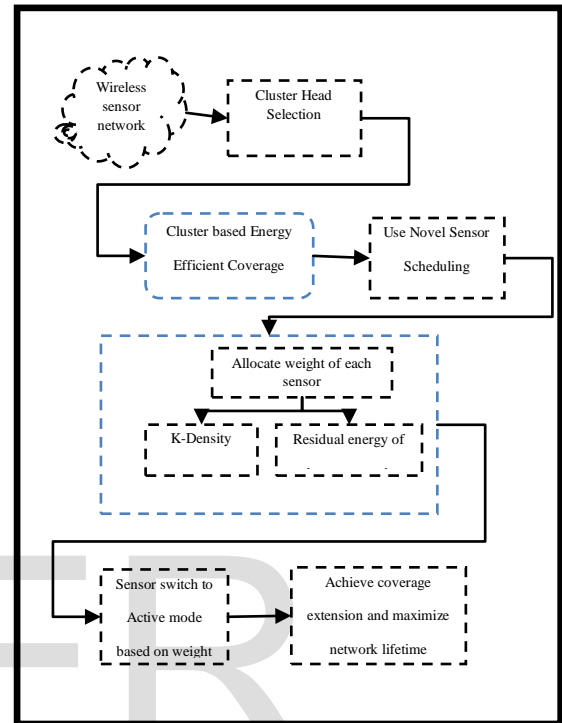


Fig1: Coverage extension in wireless sensor network

5. SYSTEM IMPLEMENTATION

5.1 Network Model

An undirected graph $G(V, E)$ where the set of vertices V represent the mobile nodes in the network and E represents set of edges in the graph which represents the physical or logical links between the mobile nodes. Sensor nodes [5] are placed at a same level. Two nodes that can communicate directly with each other are connected by an edge in the graph. Let N denote a network of m mobile nodes, $N_1, N_2 \dots N_m$ and let D denote a collection of n data items $d_1; d_2; \dots; d_n$

distributed in the network [6]. For each pair of mobile nodes N_i and N_j , let t_{ij} denote the delay of transmitting a data item of unit-size between these two nodes.

5.2 Learning automata theory

A learning automaton is an adaptive decision making unit that improves its performance by learning how to choose the optimal action from a finite set of allowed actions through repeated interactions with a random environment. The objective of a learning automaton is to find the optimal action from the action-set so that the average penalty received from the environment is minimized. The environment can be described by a triple (α, β, c) where $\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_r\}$ represents the finite set of the inputs $\beta = \{\beta_1, \beta_2, \dots, \beta_m\}$ denotes the set of the values that can be taken by the reinforcement signal, and $c = \{c_1, c_2, \dots, c_r\}$ denotes the set of the penalty probabilities, where the element c_i is associated with the given action α_i . If the penalty probabilities are constant, the random environment is said to be a stationary random environment, and if they vary with time, the environment is called a non-stationary environment. The environments depending on the nature of the reinforcement signal β can be classified into P-model, Q-model and S-model. The environments in which the reinforcement signal can only take two binary values 0 and 1 are referred to as P-model environments. Another class of the environment allows a finite number of the values in the interval [0, 1] can be taken by the reinforcement signal. Such an environment is referred to as Q-model environment. In S-model environments, the reinforcement signal lies in the

interval $[a, b]$. Variable structure learning automata are represented by a triple $\langle \beta, \alpha, L \rangle$ where β is set of inputs, α is set of actions and L is learning algorithm. The learning algorithm is a recurrence relation which is used to modify the action probability vector. Let $\alpha_i(k) \in \alpha$ and $p(k)$ denote the action selected by learning automaton and the probability vector defined over the action set at instant k , respectively. Let a and b denote the reward and penalty parameters and determine the amount of increases and decreases of the action probabilities, respectively. Let r be the number of actions that can be taken by learning automaton. At each instant k , the action probability vector $p(k)$ [7] is updated by the linear learning algorithm. If the selected action $\alpha_i(k)$ is rewarded by the random environment, and it is updated as given in Eq. (2) if the taken action is penalized.

$$p_j(k+1) = \begin{cases} p_j(k) + a[1 - p_j(k)] & \text{if } j = \alpha_i(k) \\ (1 - a)p_j(k) & \text{otherwise} \end{cases} \quad (1)$$

$$p_j(k+1) = \begin{cases} (1 - b)p_j(k) & j \neq \alpha_i(k) \\ \left(\frac{b}{r-1}\right) + (1 - b)p_j(k) & j = \alpha_i(k) \end{cases}$$

(2)

Learning automaton with a changing number of actions is absolutely expedient and also ϵ -optimal, when the reinforcement scheme is L_{R-T} . Such an automaton has a finite set of r actions, $\alpha = \{\alpha_1, \alpha_2, \dots, \alpha_r\}$. $A = \{A_1, A_2, \dots, A_m\}$ denotes the set of action subsets and A

$(k) \subseteq \alpha$ is the subset of all the actions can be chosen by the learning automaton, at each instant k . The selection of the particular action subsets is randomly made by an external agency according to the probability distribution

$$\Psi_k(k) = \Psi_1(k), \Psi_2(k), \dots, \Psi_m(k)$$

defined over the possible subsets of the actions, where

$$\Psi_i(k) = \text{prob}[A(k) = A_i | A_i \in A, 1 \leq i \leq 2^r - 1]$$

$$\hat{p}_i(k) = \text{prob}[\alpha(k) =$$

$$\alpha_i | A(k), \alpha_i \in A(k)]$$

denotes the probability of choosing action α_i conditioned on the event that the action subset $A(k)$ has already been selected and $\alpha_i \in A(k)$ too. The scaled probability $\hat{p}_i(k)$ is defined as,

$$\hat{p}_i(k) = \frac{p_i(k)}{K(k)} \quad (3)$$

Where $K(k) = \sum_{\alpha_i \in A(k)} p_i(k)$ is the sum of the probabilities of the actions in subset $A(k)$ and $p_i(k) = \text{prob}[\alpha(k) = \alpha_i]$.

5.3 Energy-efficient area coverage algorithm

Let us take triple $\langle N, L, E \rangle$ denotes the topology graph of a WSN, where $N = \{n_1, n_2, \dots\}$ is the set of sensor nodes, $L = \{l_{(n_i, n_j)}\} \subseteq N \times N$ is the set of communication links, and $E = \{E_{n_i} | \forall n_i \in N\}$ denotes the set of energies associated with the sensor nodes. Let E_{n_i} be the residual energy of sensor node n_i . LAEEC aims to construct the most-stable energy-efficient sensor network covering the monitoring area by finding a near optimal solution to the DCDS problem, where the weight of each node is defined as its residual energy level.

DCDS seeks for the set of most energetic connected sensors whose maximum degree is bounded above by d . Let $\mathcal{C} = \{c_1, c_2, \dots\}$ denotes the set of all possible degree-constrained CDSs covering the sensing area C_s is the optimal problem.

$$E_{c_s} = \min_{\forall c_i \in \mathcal{C}} \left[\frac{1}{\min_{\forall n_j \in c_i} \{E_{n_j}\}} \right] \quad (4)$$

Where E_{c_s} denotes the energy of optimal degree-constrained CDS c_s , $\min_{\forall n_j \in c_i} \{E_{n_j}\}$ denotes the energy of degree-constrained CDS c_i subject to constraint d . Energy of a degree-constrained CDS[8] is defined as the residual energy level of the most energetic active sensor.

5.4 Degree-constrained CDS-based area coverage algorithm

A fully distributed learning automata based algorithm is proposed for solving the area coverage problem in WSN by finding a near optimal solution to the degree-constrained minimum-weight[8] CDS problem. In this algorithm, a group of learning automata, named as GoL, is constituted by equipping each sensor node n_i with a variable action-set learning automaton A_i . Duple GoL is defined as $\langle A(k), \alpha(k) \rangle$, where $A(k) = \{A_i | \forall n_i \in N(k)\}$ denotes the set of learning automata assigned to the sensor nodes, and $\alpha(k) = \{\alpha_i | \forall A_i\}$ denotes the set of actions that can be taken by each learning automaton A_i . The node that is running the algorithm is called the current node. At each instant k , each

current node n_i discovers its neighbors and forms its action-set by sending an ASF (action-set formation) message. Each node that receives the ASF message replies it. The reply message includes the residual energy level of the node. Current node n_i forms its action-set based on the received replies. Due to the network topology changes, one node may leave (or join to) the other node at each stage. If link $l_{(n_i, n_j)}$ breaks at stage $k + 1$, its corresponding action. Moreover, the choice probability of the other actions must be updated as

$$p_i^j(k+1) = \frac{p_i^j(k)}{1 - p_i^j(k)} \quad \text{In}$$

automation A_i . When a new link $l_{(n_i, n_j)}$

is established at stage $k + 1$, the choice probability of the new action is initialized to $1/|\alpha_i(k+1)|$, and that of the other actions is updated as

$$p_i^j(k+1) = p_i^j(k) \cdot \left[\frac{|\alpha_i(k+1)| - 1}{|\alpha_i(k+1)|} \right].$$

Let C_k denotes the degree-constrained CDS that is constructed at stage k . Let C_k' be the set of sensor nodes covered by C_k . C_k is initially set to n_i and C_k' is initialized to n_i and its one-hop neighbors. E_{C_k} is initialized to E_{n_i} . Let

d_k denotes the average degree of C_k . d_k is defined as $[\sum_{n_i \in C_k} \Delta_i(k)]/|C_k|$ at each stage k , where $\Delta_i(k)$ denotes the degree of node n_i at stage k . Then node

n_i compares the residual energy level of sensor node n_j with average energy level and average degree d_k with degree-constraint d . Then n_i updates the internal state of its automaton according to the following updating rules. If the residual energy level of the node selected by n_i is higher than the average

energy level of the neighbors of n_i and d_k does not exceed degree-constraint d , learning automaton A_i rewards the selected action. If the energy level of selected node n_j is lower than the average energy level and the average degree d_k is larger than degree-constraint d , learning automaton A_i penalizes the selected action.

5.5 Cluster-based efficient-energy coverage scheme

In the purpose to ensure the area coverage while prolonging network lifetime, we proposed a cluster-based distributed scheme called CSA_VS (Cluster-based Scheduling Algorithm – Virtual Sensor)[10], which is used to allow each sensor to switch between active and sleep modes to save energy. Sensors are assumed that they have limited battery energy. Sensing, transmitting and receiving activities consume battery energy of a sensor, and thus limit the network lifetime. In this work, we determine the statute of all the deployed sensors to be either active or sleep based on their capabilities as well as the state durations, such that the network lifetime is maximized.

5.6 Performance Evaluation

In this section the performance of the existing and the proposed system is compared. In the existing system, degree-constrained minimum-weight extension of the CDS problem called DCDS to model the area coverage in WSNs. In the proposed system, Cluster-based Scheduling Algorithm–Virtual Sensor [9] is proposed to achieve energy saving.

6. Result and Discussion ENERGY CONSUMPTION

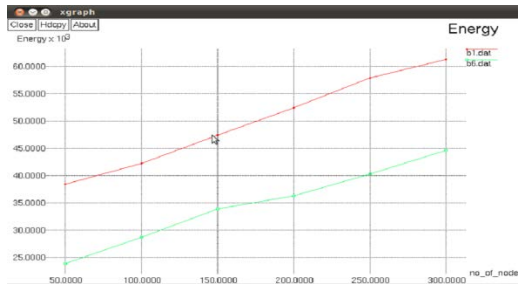


Fig4.1 The energy consumption is shown in this graph. In the X-axis number of nodes is taken. Y-axis energy consumption is taken. This graph clearly shows that if the number of nodes is increases the energy consumption is increased in the existing system. But in the proposed system, there is less energy consumption

COVERED NODES

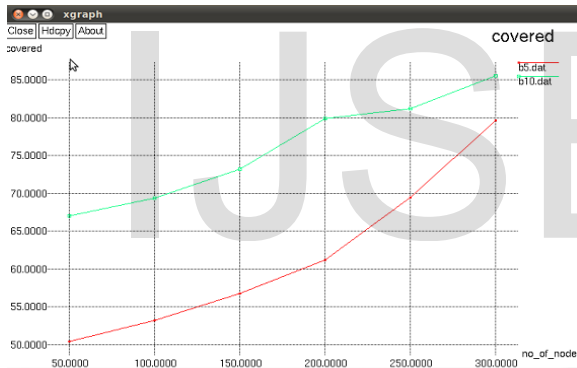


Fig 4.2 The number of covered nodes is shown in this graph. In the X-axis number of nodes is taken. Y-axis number of active nodes is taken. This metric is defined as the average number of nodes that are activated to cover the sensor field. This graph clearly shows that if the number of nodes is increases the number of covered nodes is decreased in the existing system. But in the proposed system, there is number of covered nodes is increased.

LIFETIME

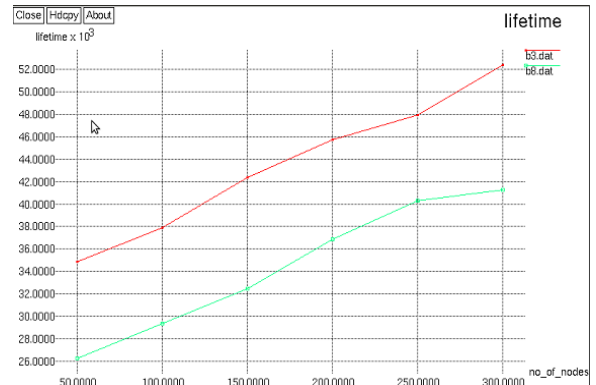
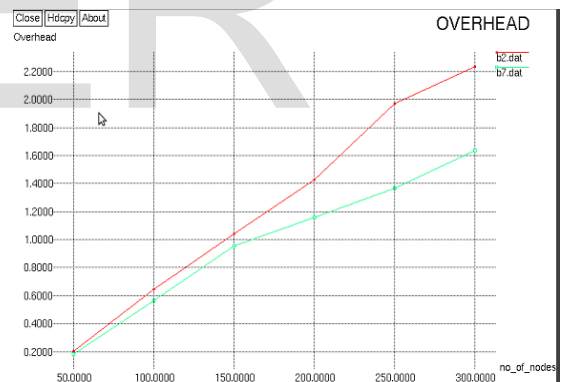


Fig 4.3 The Lifetime of the network is shown in this graph. In the X-axis number of nodes is taken. Y-axis Lifetime of the network is taken. This graph clearly shows that if the number of nodes is increases the Lifetime of the network is decreased in the existing system. But in the proposed system, there is Lifetime of the network is increased.

OVERHEAD



The overhead is shown in this graph. In the X-axis number of nodes is taken. Y-axis overhead is taken. This graph clearly shows that if the number of nodes is increases the overhead is increases in the existing system. But in the proposed system, there is less overhead.

7. CONCLUSION AND FUTURE WORK

7.1 Conclusion

CDS has received a lot of attention and found many applications in wireless networking such as routing, clustering, backbone formation, and multicasting. CDS has recently emerged as an innovative approach to model the area coverage problem in wireless sensor networks and several CDS-based area coverage protocols have been proposed. However, the major problem affecting the performance of the existing CDS based coverage protocols is that they aim at maximizing the number of sleep nodes to save more energy. This work proposed a degree constrained minimum-weight extension of the CDS problem called DCDS to model the area coverage problem in WSNs. Selection of an optimal degree-constraint for the DCDS balances the network load on the active nodes and improves the network coverage, connectivity, and lifetime. This work designed a learning automata-based heuristic called LAEEC for finding a near optimal solution to the proxy equivalent DCDS problem in WSN. In addition to that, a cluster-based efficient-energy coverage scheme called CSA_VS to ensure the full coverage of a monitored area while saving energy. For future research, it is planned to use service differentiation in the coverage extension based on incentive scheduling approach. Service differentiation is a method for specifying and controlling network traffic by class so that certain types of traffic get precedence - for example, voice traffic, which requires a relatively uninterrupted flow of data, might get precedence over other kinds of traffic. It provides dynamic prioritized access to users for service differentiation in a quantifiable manner.

REFERENCES

- [1] Y. Zeng, C.J. Sreenan, N. Xiong, L.T. Yang, J.H. Park, Connectivity and coverage maintenance in wireless sensor networks, *Journal of Supercomputing* 52 (2010) 23–46.
- [2] S. Sengupta, S. Das, M.D. Nasir, B.K. Panigrahi, Multi-objective node deployment in WSNs: in search of an optimal trade-off among coverage, lifetime, energy consumption, and connectivity, *Engineering Applications of Artificial Intelligence* (2012).
- [3] C. Zhu, C. Zheng, L. Shu, G. Han, A survey on coverage and connectivity issues in wireless sensor networks, *Journal of Network and Computer Applications* 35 (2012) 619–632.
- [4] S. Rizvi, H.K. Qureshi, S.A. Khayam, V. Rakocvic, M. Rajarajan, A1: an energy efficient topology control algorithm for connected area coverage in wireless sensor networks, *Journal of Network and Computer Applications* 35 (2012) 597–605.
- [5] M.A. Guvensan, A.G. Yavuz, On coverage issues in directional sensor networks: a survey, *Ad Hoc Networks* 9 (2011) 1238–1255.
- [6] P.M. Wightman, M.A. Labrador, A family of simple distributed minimum connected dominating set-based topology construction algorithms, *Journal of Network and Computer Applications* 34 (2011) 1997–2010.
- [7] H.M. Ammari, S.K. Das, Centralized and clustered k-coverage protocols for wireless sensor networks, *IEEE Transactions on Computers* 61 (1) (2012) 118–133.

[8] M. Hefeeda, H. Ahmadi, Energy-efficient protocol for deterministic and probabilistic coverage in sensor networks, IEEE Transactions on Parallel and Distributed Systems 21 (5) (2010) 579–593.

[9] S. Misra, M.P. Kumar, M.S. Obaidat, Connectivity preserving localized coverage algorithm for area monitoring using wireless sensor networks, Computer Communications 34 (2011) 1484– 1496.

IJSER