Journal of Network and Computer Applications 122 (2018) 128–136

Contents lists available at ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

Learning automaton based topology control protocol for extending wireless sensor networks lifetime

Mahmood Javadi [a], Habib Mostafaei [b,*], Morshed U. Chowdhurry [c], Jemal H. Abawajy [c]

[a] *Sama technical and vocational training college, Islamic Azad University, Khoy Brach, Khoy, Iran*
[b] *Department of Engineering, Roma Tre University, Rome, Italy*
[c] *Faculty of Science, Engineering and Built Environment, Deakin University, Australia*

ARTICLE INFO

Keywords:
Topology control
Learning automaton (LA)
Sensor transmission
Energy efficiency

ABSTRACT

Energy efficiency is one of the critical challenges in wireless sensor networks because the nodes in such networks have limited resources. Therefore, they should be managed efficiently in order to exploit the network's functionality for a longer period of time. Topology control mechanisms can help the nodes to leverage their resources efficiently. Several topology control protocols for WSNs have been proposed to decrease energy consumption of the nodes and increase the network capacity. Leveraging a lower transmission range can help the nodes to mitigate their energy consumptions. In this paper, we propose a topology control protocol based on learning automaton, which is named LBLATC. The learning automaton of every sensor node chooses the proper transmission range of the node using the reinforcement signal which is produced by the learning automaton of neighbor sensor nodes. The simulation runs carried out to verify the performance of the proposed protocol. It acts on average 15% better than current state-of-art in term of selecting a proper transmission range.

1. Introduction

Wireless sensor networks (WSNs) have been widely used in many fields like surveillance systems, detecting unexpected events, environmental monitoring, military, etc. (Yang, 2014). The proliferation of these network creates Internet of Things (IoT) (Gubbi et al., 2013). As such, WSNs are widely used in IoT applications to gather the information around us. Sensor nodes in WSNs have many resource limitations such as battery, computation, etc. Therefore, it is necessary to save their resources in order to use the network for a long period of time. Thus, energy efficiency is a key issue in these networks (Mostafaei and Menth, 2018; Pantazis et al., 2013). Coverage and topology control algorithms have impact on the lifetime of WSNs. Therefore, coverage and topology control algorithms have been considered in many research works. For example, a learning automaton based method to meet the coverage requirements of a network is proposed in (Mostafaei et al., 2017) to improve overall lifetime of the network.

In this paper, we consider the problem of extending wireless sensor networks (WSNs) lifetime. As data transmission constitutes the highest energy consumption tasks in WSNs, an efficient mechanism for data transmission in WSNs is a common approach for optimizing the energy usage of sensor nodes. Therefore, one of the main objectives of topology control mechanisms in WSNs is to coordinate the network's nodes by choosing a suitable transmission range for them. This helps in creating a network with few links between the nodes. Therefore, the energy consumptions are minimized and the network lifetime can be increased. As suitable topology can boost the performance of a network, several protocols have been proposed to adjust the transmission ranges of nodes in sensor networks (Zhang et al., 2015; Lin et al., 2016; Li et al., 2013). The quality of the selection differs according to different priorities and conditions. Each selection criteria can have different performance because it has a direct effect on energy consumption of the nodes. One of the advantages of adjusting the transmission range is that the obtained topology is not too dense. Therefore, exploiting less dense work results in having less intermission among the selected nodes which is not considered by recent state-of-art works in (Aziz et al., 2013; Santi, 2005; Abolhassani et al., 2009).

In homogeneous networks, all nodes have the same transmission range. However, these networks do not have a proper efficiency, durability, and robustness. Heterogeneous networks, also, use sensors with the same transmission ranges, and, despite the density in neighboring sensors, each sensor chooses its own transmission range to maintain the

* Corresponding author.
E-mail addresses: javadi.mahmood@gmail.com (M. Javadi), mostafae@dia.uniroma3.it (H. Mostafaei), muc@deakin.edu.au (M.U. Chowdhurry), jemal.abawajy@deakin.edu.au (J.H. Abawajy).

https://doi.org/10.1016/j.jnca.2018.08.012
Received 29 January 2018; Received in revised form 7 July 2018; Accepted 22 August 2018
Available online 29 August 2018
1084-8045/

network connectivity. As a result, such networks are more robust and efficient than homogeneous ones (Aziz et al., 2013; Santi, 2005).

In this paper, we propose a topology control protocol based on learning automaton. The proposed algorithm considers the network density to select the transmission range for every node and these transmission ranges are not the same for all nodes. The main contribution of this paper can be summarized as follows; i) We model the topology control problem with the network of learning automaton; ii) We propose a novel algorithm to select appropriate transmission ranges for sensor nodes, and iii) We demonstrate the efficacy of the proposed algorithm through extensive simulation to validate that the proposed algorithm saves the sensor node energy and consequently improves the network lifetime. Our algorithm can be applied for the monitoring applications such as military zone monitoring to track the objects and vehicles, and all monitoring applications that suffer from efficiency. The rationale behind using the learning automaton is that it requires $O(n)$ to solve an NP-hard or an NP-complete problem (Mostafaei et al., 2017).

The rest of the paper is organized as follows. Section 2 briefly reviews the related work. Problem definition stated in Section 3. In Section 4, the learning automaton theory is presented. Section 5 presents the proposed algorithm. Section 6 shows the performance of the proposed algorithm through simulations. Section 7 concludes the paper.

2. Related work

Energy-efficient topology control algorithms proposed for WSN are classified in four different groups (Torkestani, 2013; Li et al., 2013): i) power-adjustment approach, ii) power-mode approach, iii) clustering approach and iv) hybrid approach. The power-adjustment approach is the most common form of the topology control in which each sensor node dynamically adjusts the transmission range of its radio to minimize the power consumption during transmission. In this approach, the adjacent sensor nodes try to find the appropriate (lowest possible) transmission range to keep the network connected. The aim here is to find the minimum range of transmission so that the qualities of a good network are guaranteed.

The protocols themselves are categorized into three groups. The first one contains location-based protocols like (Santi, 2005; Li et al., 2005; Zhang et al., 2016). In these protocols each network node knows its own exact location using GPS and can create a proper topology for the network. The second group pertains to location-based protocols. Here, the nodes do not have the exact information about their location but are able to detect the direction of their neighbors (Santi, 2005). The third group contains the neighbor-based protocols in which the nodes have limited information about their neighbors. This information can be the ID number, distance, or quality of the neighbors such protocols in *Kneigh* (Blough et al., 2003) and *XTC* (Wattenhofer and Zollinger, 2004). Another topology control protocol is $RAA-2L$ in which each node chooses either R_s or R_w ($R_w < R_s$) to be its transmission range. If the node of R_w can communicate with that of R_s, the node chooses R_w, otherwise it chooses R_s. In $RAA-3L$ the node chooses one of the R_w, R_s or R_t($R_w < R_t < R_s$).

The reliable topology control in WSNs has been studied in (Lee et al., 2013; Khalil and Ozdemir, 2017; Haque et al., 2015; Deniz et al., 2016). Lee et al. (2013) devised a distributed topology construction mechanism for the reliable topology control issues which the proposed algorithm takes energy efficiency into consideration for real applications. The proposed algorithm can maintain the connectivity of the nodes in the network and it can also extend the network lifetime. Haque et al. (2015) used the graph theory concepts to provide a reliable topology for a WSN to minimize the network energy consumption. They proposed various algorithms like *minimum spanning tree* and *shortest path tree* methods for data delivery in a WSN.

A PSO-optimized, minimum spanning-tree based topology control scheme is proposed in (Guo et al., 2013). In the proposed scheme, they transformed the problem into a model of multi-criteria degree constrained minimum spanning tree (MCD-MST) and designed a non-dominated discrete particle swarm optimization (NDPSO) to deal with this problem.

Cluster-based topology control have been studied by researchers in (Leu et al., 2015; Jameii et al., 2016). The concept of clustering helps algorithms to construct more scalable topology control protocols which are easily manageable. In the clustering approaches nodes are divided into clusters and in each cluster only the cluster-head is responsible for handling the communications. A cluster member can be activated when it is required. This concept aims at minimizing the number of required active nodes in the network.

The concept of Connected Dominating Set (CDS) has been often leveraged. A CDS is a subset of vertices such that every vertex is either in the subset or adjacent to a vertex in the subset and the subgraph induced by the subset is connected. In this approach CDS nodes can be active to maintain the network requirements while non-CDS nodes remain idle state to save their energy. In a CDS based algorithm for WSNs each node in the network is either a member of CDS or a neighbor of a node in CDS. Ma et al. (2007) used a minimum connected dominating set approach to construct an energy efficient topology control protocol in WSNs. Their protocol used the shortest path approach to find a path from every node in the network to sink node. Qureshi et al. (2013) performed a three CDS based approaches for the topology control based the number of messages, the energy overhead, the amount of residual energy, the number of unconnected nodes, and convergence time. Mostafaei et al. (2015) proposed a degree constraint dominating set approach to control the nodes of the network in order to improve the lifetime of a WSN providing partial coverage.

In this paper, we leverage learning automaton to select a suitable transmission range for each node by considering the energy consumptions of the nodes because adjusting the transmission range of each node has a determinant impact on nodes energy consumption. Therefore, we exploit this fact to devise our algorithm. Learning automaton of each node is in charge of choosing the transmission range.

Table 1
Notations of this work.

Symbols	Definitions
$S(L \times W)$	The network area
N	The number of nodes in the network
n_i	A simple sensor
R_1	The low power transmission range of sensor n_i
R_t	The high power transmission range of sensor n_i
A_1	A set of 60% of neighbors
A_t	A set of all neighbors
N_i	the number of neighbor nodes of node n_i
D_{ni}	distance between the neighbor node and the current node
p_i	the average transmission power of node i
p_{avg}	the average transmission power of all nodes
$e_i(t)$	the residual energy of node i at time t

3. Problem overview

In this section, we state the required definitions for the topology control problem and formal definition of the considered problem. Table 1 shows the symbols that are used in this paper.

Wireless Sensor Network (WSN) is composed of N randomly deployed nodes in a two-dimension network with size of $L \times W$ where L and W are the length and width of the network area, respectively. Each node can sense the environment within its sensing range (R_s) and can communicate with the nodes within its transmission range.

Transmission ranges. In this paper, we assume that every node has two different transmission ranges. Each sensor node can choose one of these two ranges arbitrarily as the transmission range which is determined based on the density of nodes with their maximum transmis-

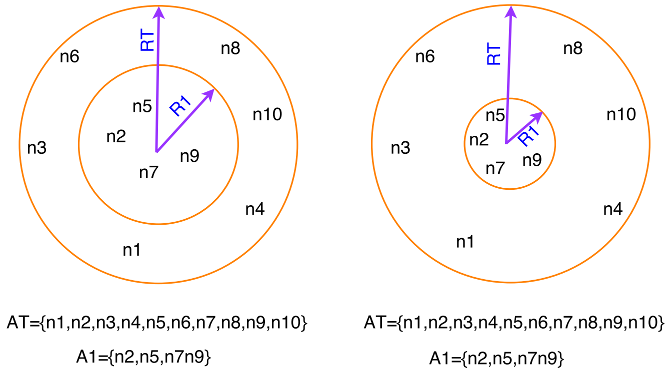


Fig. 1. Two sample nodes with different transmission and identical collections are shown by comparing the right and left figurer and determining the range of different nodes; nodes dispersion method in determining the range of each node is effective.

sion range. The transmission range with low power denoted as R_1 and one with high power denoted as R_t where $R_1 < R_t$. In this model, the number of nodes with R_1 as transmission range is proportionate to the number of neighbor nodes (i.e., the density of each node). For example, in Fig. 1 node n_{11} has two transmission ranges. The number of nodes with R_1 transmission range is equal to the distance that covers 0.6 of all the neighbors in the maximum range of that node. The number of R_t is equal to the maximum range of nodes. When the distance between two nodes is less than the amount of R_t, those two nodes will be considered as neighbors. Every node puts its neighbors in two different sets, namely, A_1 and A_t sets. They are divided by the following equations (Eq. (1)). In this equation, N_i is the number of neighbor nodes, and D_{ni} is the distance between the neighbor nodes (n_i) and the current node.

$$\begin{cases} N_i \in A_1 & if \quad D_{ni} \le R_1 \\ N_i \in A_t & if \quad D_{ni} \le R_t \end{cases} \tag{1}$$

Let assume that node n_{11} has ten nodes in its neighborhood. According to our model, the transmission range R_1 covers 60% of the nodes which includes six nodes. In the meantime, R_t includes all the nodes in the neighborhood of this node. Therefore, we have six nodes in A_1 and ten nodes in A_t sets.

We give an example to demonstrate the impact of selecting a proper transmission range for each node. Fig. 1 demonstrates an example of a network with eleven nodes. As it was shown in the right-hand side figure decreasing the transmission range does not change the A_1 and A_t sets, but it can help to save residual energy of the node. The reason for this result relies on using a lower transmission range for each node because the energy consumption of each node is determined based on this parameter. Therefore, having a longer transmission for each node results in using more energy from that node. Fig. 2 shows an example of applying topology control algorithm on a network without loss of connectivity of the nodes. As it is clear from Fig. 2, reducing the transmission range of the node has not any effect on the connectivity of the nodes but it aims to save the energy of the nodes.

Formal definition of the problem. Given a randomly scattered network with N nodes, the considered topology control problem is the choice of minimum transmission range (i.e., R_1 or R_t) for each node in such a way that the energy consumption of the node is minimized. Assume that P_{avgi} is the average transmission power of node i. Then, the object is to minimize the average transmission power (p_{avg}) of all nodes which is defined as follow;

$$p_{avg} = \frac{\sum_{i=1}^{n} p_i}{n} \tag{2}$$

where, p_i is the transmission power of node i and n is the number of nodes in the network. By considering Eq. (2), the overall energy of the network is defined as a function of z and can be computed by:

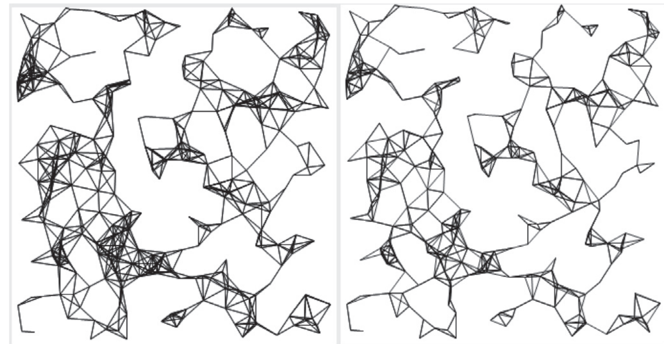


Fig. 2. Left network topology before the execution of the protocol vs. the right network topology after.

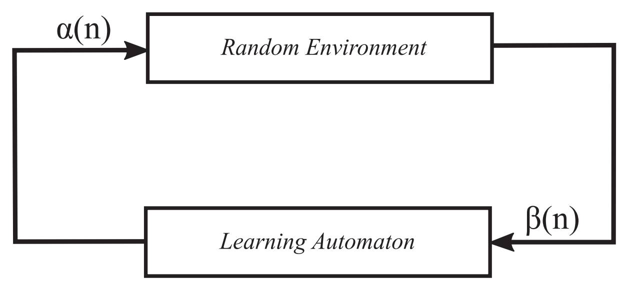


Fig. 3. Stochastic automaton.

$$e(z,t) = \lim_{t\to\infty} \frac{1}{S} \sum_{\forall n_i \in N}^{n} e_i(t) \tag{3}$$

in which S is the network area and $e_i(t)$ is the residual energy of node i at time t, respectively. Therefore, the objective of this is to minimize the power consumption of the nodes and maximize the overall lifetime of the network.

$$\begin{aligned} &\min p_{avg}, \\ &\max e(z,t) \end{aligned} \tag{4}$$

4. Learning automaton

We can consider the automaton as abstract objects that can perform a specific number of actions. Every time this object chooses one action among a collection of actions, its performance is evaluated in a random environment, and the achieved answer of the environment is used to choose the next action of the automaton. During this process the automaton learns to choose the optimal action (Narendra and Thathachar, 1989) among its action set. Using responses provided by the environment depends on the automaton's selected action. In this way, the automaton identifies the optimal action slowly. The implemented method obtained through the environment's answer to choose the next action is determined by the learning algorithm. Every learning automaton is composed of two main parts hat are seen in Fig. 3.

1. A random automaton has limited numbers of actions and is communicating with a random environment.
2. Learning algorithm through which the automaton identifies the optimal action.

We can consider every Automaton as a finite machine, i.e. $SA = \{\alpha, \beta, F, G, \phi\}$. In this equation,$\alpha$ is the set of automaton actions among which the automaton chooses one in every iteration. β is entrance set which defines the automaton input. F and G map the current state and input onto the next action that has been selected by the automaton.

4.1. Environment

Stochastic environment is shown in a mathematical way by tree members of E set $E = \{\alpha, \beta, c\}$ in which $\alpha = \{\alpha_1, \alpha_2, \dots\}$, $\beta = \{\beta_1, \beta_2, \dots\}$, and $c = \{c_1, c_2, \dots\}$. In this equation, α is the environment input set, while β represents the set of environment output. Different models have been defined for stochastic environments. The relation between stochastic environment and stochastic automaton has been shown in the following Fig. 3.

4.2. Learning algorithm

As it is shown in the figure above, we can describe a learning algorithm as following.

$$p(n+1) = T[p(n), \alpha(n), \beta(n)] \tag{5}$$

In the equation above, if T is linear, the algorithm is also linear; otherwise, it is nonlinear. We can say that the main idea of all learning algorithms is as follows.

If automaton in N iteration chooses α_i action and receives desired answer for it form the environment, $p_i(n)$ probability related to that action will increase, and probabilities of the other actions will decrease. But, if it receives an undesirable answer, $p_i(n)$ will decrease, and probabilities related to the other actions will increase. So, for a desired answer f_i and g_j are non-negative functions and are called as reward and penalty functions.

$$p_j(n+1) = \begin{cases} p_j(n) + a(1 - p_j(n)) & j = i \\ (1-a)p_j(n) & \forall j, j \neq i \end{cases} \tag{6}$$

For an undesirable answer:

$$p_j(n+1) = \begin{cases} (1-b)p_j(n) & j = i \\ \dfrac{b}{r-1} + (1-b)p_j(n) & \forall j, j \neq i \end{cases} \tag{7}$$

where a and b are reward and penalty parameters, respectively. In these equations, r determines the number of action for each LA. In (Mostafaei et al., 2015, 2017), some usages of learning automaton in the field of wireless sensor networks are introduced.

5. Proposed protocol

The proposed location-based protocol of topology control through the use of learning automaton has three phases: starting phase, learning phase, and select-best-action phase. In the first phase, each node initializes its internal data structure by sending a suitable packet within its transmission range and receiving the answer from the neighbors. Forming the action-set of each node and updating the probability of each action are carried out in learning phase. Finally, selecting the best action by learning automaton of each node to determine the final transmission range is performed in select-best-action phase. We explain each of these phases in this section.

Each node in LBLATC algorithm has a data structure to store the following information. 1) A_t, a list of neighbors that are within R_t distance from this node, 2) A_1, a list of neighbors that are within R_1 distance from this node, and 3) K, a counter which counts the iteration of algorithm. Algorithm 1 illustrates the pseudo code of our algorithm.

5.1. Starting phase

In this phase, every node with maximum transmission range (R_t) sends a hello packet with its own information, including the identification number and location. In this way, every node gets their neighbor's information. Every node, according to the received information from the neighbors, calculates their distance to itself. Based on the calculated distance, every node gets the number of neighbors around it. According to the number of neighbors that is located in each node range, the node determines the R_1 range. Then, the nodes put their neighbors in A_t or A_1 sets based on their distance to their neighboring nodes. Consequently, it updates the corresponding values in its data structure.

Here, every sensor gets two allowed transmission ranges based on the information they receive. One of the ranges is the maximum transmission range, and the other one is the range that every sensor covers 0.6 (60%) of its neighbors. As best of our knowledge, none of the previous state-of-the-art methods considered the density of sensors in selecting a transmission range. This is the first attempt to involve the nodes density to in selecting the proper nodes to maintain the backbone of the network to transfer the information.

5.2. Learning phase

In learning phase, nodes choose their transmission range according to the condition of their sets and the transmission range of the other nodes. At the beginning, every sensor is equipped with the learning automaton, and the number of actions in the automaton is equal to two. The first action corresponds to selecting R_1 and the second action refer to R_t as the transmission range of each node. At the end of learning phase, learning automaton of each node select its best action based on the probability of it.

Learning automaton (LA) in each node chooses an action randomly, and then sends a `action` packet with selected transmission range to its neighbors. Every `action` packet contains the node id and its location information. At the next phase, nodes make an effort to answer the `action` packet according to the received `action` packet. The `action` packet answer includes the range, id and neighbors listed.

At the last phase, every node examines whether the whole neighbor is located in its selected range and if the neighbor list, which is received from the neighbor, covers all the neighbors located in its maximum range or not.

This information is leveraged as the reinforcement signal for our algorithm. If the selected range covers the neighbors which are located in the maximum range, the node will reward its selected range according to Eq. (6); otherwise, the probability of selected action will be updated by using Eq. (7). Our algorithm objective is to find maximum range for each node to cover neighbors. The reason to apply this is that the algorithm uses minimum number of nodes to obtain the network information. Consequently, in our topology control solution the reward function is used to help the nodes to find their best transmission ranges.

Note that when LA of nodes receive reward for the selected actions this means that the environment response is 0 (i.e. $\beta = 0$). In this state, LA of each node uses eq. (6) to update its action probability vector according to (Narendra and Thathachar, 1989). Otherwise, the environment response is 1 (i.e $\beta = 1$) and LA of each nodes uses Eq. (7) to update the action probability vector.

5.3. Select-best-action phase

The action of choosing the range is repeated until one transmission probability exceeds the threshold limit or is repeated for 100 times which is obtained empirically. Eventually, the range of every node that has gained the most probability in learning phase becomes the final range for data transmission. Indeed, the LA of each node in this case selects its best action among action-set and based on the returned action by LA of each node, it will select the proper range for steering information. It worth stating that LBLATC algorithm leverages the LA of each node to check the number of neighbors within its neighborhood. Using a short transmission range without disconnecting from neighbors aims at energy saving for LBLATC.

To prove the convergency of proposed protocol we can use the same method in (Narendra and Thathachar, 1989). The basic theoretical question in the operation of a LA is the asymptotic behaviour of p(n)

Algorithm 1 LBLATC Algorithm.

```
Input:
    A Network with N nodes                          ▷ Each node is equipped with a learning automaton
    a and b as the learning parameters              ▷ Parameters for Eq. 6 and Eq. 7
Output:
    an appropriate transmission range for each node ▷ Each node will select either R_1 or R_t
/* the starting phase */
for each node n_i in N do
    Send a Hello packet with R_t
    if n_i receives a Hello packet then
        calculate the distance from the sender;
        check the distance with R_1
        put the sender either in A_1 or A_t.
    end if
end for
/* the learning phase */
k=0
while (k ≤ 100) do
    k=k+1
    /* form action-set of each LA */
    set α_1 = 0.5 and α_2 = 0.5                     ▷ α_1 corresponds to selecting R_1 and α_2 to choose R_t
    select an action randomly                       ▷ each action corresponds to either R_1 or R_t
    send an action packet with selected transmission range
    wait for the answers to action packet
    gather all answer packets
    examine the neighbors id from the answer packets
    if all neighbors are within the packets then
        β_i(n) = 0                                  ▷ Reward from the environment
        update the probability of action according to Eq. 6
    else
        β_i(n) = 1                                  ▷ Penalty from the environment
        update the probability of action according to Eq. 7
    end if
end while
/* select-best-action phase */
for each node n_i in N do
    select its best action
    if best action=α_1 then
        choose R_1 as transmission range for n_i
    else
        choose R_t as transmission range for n_i
    end if
end for
```

with respect to n. It refers to the convergence of a sequence of dependent random variables. The performance of any LA based algorithm is very sensitive to learning rate of the learning algorithm. Large value for learning rate results in increasing convergency speed and decreasing the accuracy of the algorithm. While small value for learning rate results in increasing the accuracy and decreasing convergency speed of the algorithm. The same convergency proof for LA of each node can be found in (Misra et al., 2014).

5.4. A running example

In this section, we provide a running example for our proposed algorithm in order to clarify its functionality in selecting the proper transmission range for each node. Consider the network in Fig. 1. In this figure, we have 11 sensor nodes. The LA of each node has two actions which are called R_1 and R_t. At the beginning of the algorithm, the probability of each action sets to 0.5. This means that the chance of choosing each action by LA of each node is equal.

At the learning phase, each node randomly selects an action. Suppose that node N_{11} chooses action R_1. It sends an action packet to its neighbors and waits for the response for it. Each neighbor follows the same procedure to choose an action. This means that each neighbor selects a random action among its action set and provides an answer to that packet. If the neighbors with the chosen action are in the neighbor list of this node the LA of this node updates its action probability vector according to Eq. (6). This results an increment of the probability of this action. This procedure continues until the stop condition meets. At the end of learning phase, each node will select its best action. For instance, in our example the probability of R_1 is greater than that of R_t and this results in selecting R_1 as the final transmission range for node n_{11} in our algorithm. Fig. 4 shows the flowchart of our algorithm.

6. Performance analysis

In this section, the performance of the proposed algorithm is compared against $RAA-3L$ and $RAAA-2L$ (Blough et al., 2003), *CLATC* (Abolhassani et al., 2009), and *HOM* (Stauffer and Aharony, 1994). We chose these algorithms to compare with LBLATC as they have in common the network model.

During the simulation, nodes randomly have been distributed in an area of 1000 × 1000 m. The numbers of nodes were 200, 300, 400, 500 and 600. Every node has two different transmission ranges: R_1 and

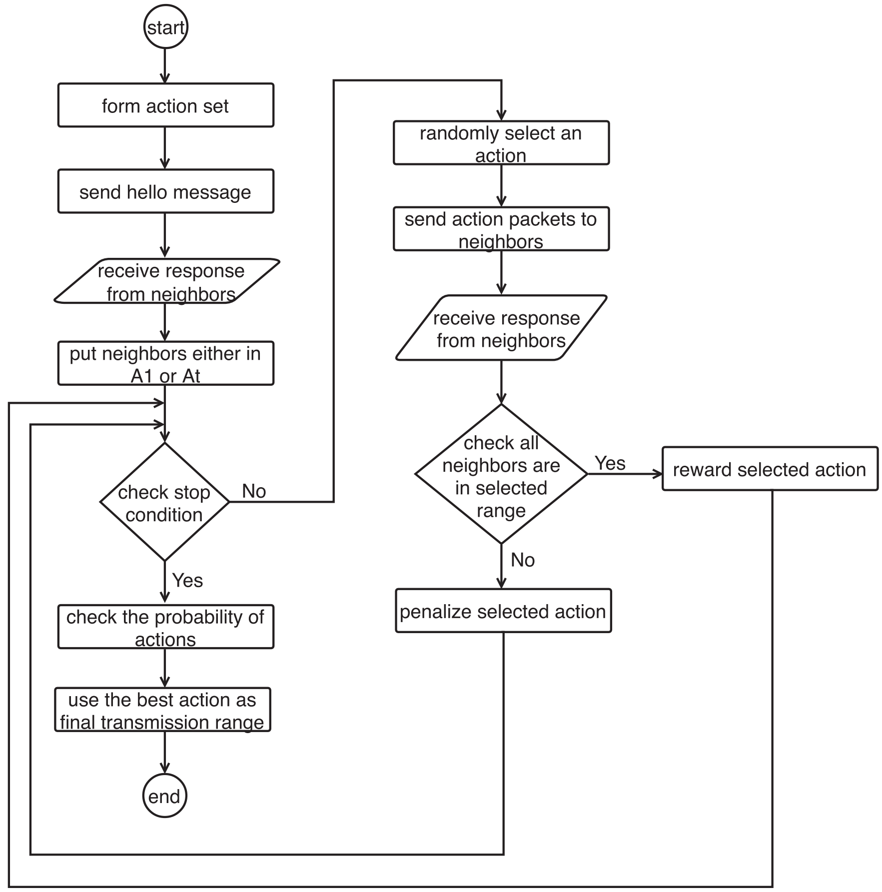


Fig. 4. Flowchart of the usage of learning automata in selecting the transmission range for each node.

R_t. R_t transmission range (in proportion to the network density) was 109 m (for 200 nodes), 86 m (for 300 nodes), 74 m (for 400 nodes), 67 m (for 500 node), and 60 m (for 600 nodes). R_1 transmission range was distinguished according to the number of current neighbors. Reward and penalty parameters were set at 0.15 and 0.3, respectively.

The authors of (Akhtar and Rehmani, 2015) provide a survey on energy model for different applications of WSNs. However, we used the energy model in (Heinzelman et al., 2002) as the reference energy model for our simulations. The required energy for the sender or receiver in this model is $E_{elec} = 50nj/bit$ and the sender amplifier needs $E_{amp} = 100pj/bit/m^2$. The required energy for transferring k bits data packet from node A to node B is as follows.

$$E_{Tx}(k,d) = E_{elec}(k) + E_{amp}(k,d)$$
$$E_{Tx}(k,d) = E_{elec} * k + E_{amp} * k * d^2 \quad (8)$$

where d is the distance between node A and node B. The required energy for to receive k bits packet is computed as follows.

$$E_{Rx}(k,d) = E_{elec}(k)$$
$$E_{Tx}(k,d) = E_{elec} * k \quad (9)$$

All simulations are performed in wireless sensor network simulator in (Wireless Sensor Networks Simulator, 2017). Table 2 shows the simulation parameters.

According to the network size, *CLATC*, $RAA-2L$, and $RAA-3L$ protocols, as well as *HOM* have been examined based on three criteria: average transmission range, average node degree (node neighbors), and average remaining energy. On average, the results were performed under examination protocols for 100 different random configurations of nodes. The results were averaged over these runs and the total number of iteration for each action of learning automaton is 100.

Table 2
Simulation parameters.

Parameter	Value
Network area	1000 × 1000
Number of nodes	200–600
Transmission range	60–109
Propagation Model	TwoRayGround
MAC Protocol	802.15.4
reward parameter (a)	0.15
penalty parameter (b)	0.3

6.1. Performance of LBLATC

The purpose of this experiment is to gain the X parameter (i.e., transmission range choice rate) for the proposed protocol. The Parameter was chosen in a way that hid the minimum selected transmission range, the minimum neighbor degree, and the maximum remaining energy. As it's evident from Fig. 5, when the parameter is 0.6, the proposed protocol has the minimum selected transmission range, the minimum neighbors, and the maximum selected transmission range. In the simulation performed to gain the best transmission range, choosing rate shows that the transmission range diagram has the minimum transmission range when the network has 200 sensors with 109 m of density, 0.15 of reward rate, 0.3 of penalty rate, and 0.6 of range selection rate.

The average transmission range for sensors was proposed for our protocol. In performed simulation, to gain the best transmission range when the chosen range rate was high the network had 200 sensors with 109 m of density. In this case we set the reward rate to 0.15 and the penalty rate to 0.3 because a low transmission range cause less conflict.

We investigate the effect of choosing the transmission range on network density. Fig. 5a shows that choosing 0.6 as the transmission range

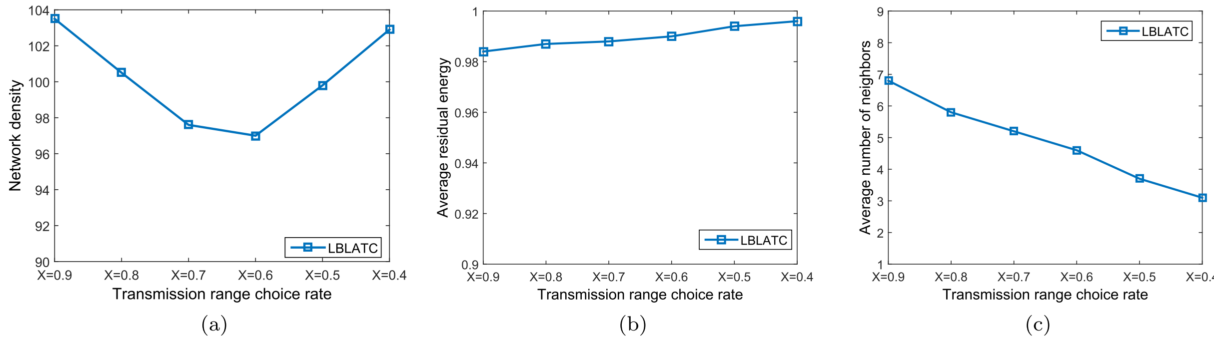


Fig. 5. The performance of our algorithm. a) the average transmission range of sensor nodes. b) the average of remaining energy in network sensor. c) the average of neighbor degree.

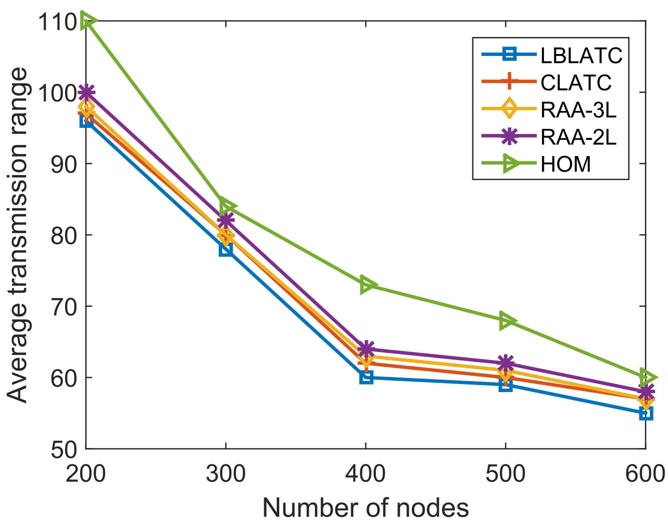


Fig. 6. Average transmission range of network nodes for LBLATC, CLATC,RAA-3L, RAA-2L, and HOM protocols in different network sizes.

for each node has the best result in network density. Therefore, each node requires to communicate with less number of nodes by choosing 0.6 of its transmission range. Fig. 5b depicts that choosing a low transmission range for the sensor nodes results in having higher remaining energy for the nodes. This fact has two reasons. First, the nodes with lower transmission range consume less energy to communicate with their neighbors. Second, choosing a low transmission range results in having less number of neighbors. Fig. 5c illustrates that the average number of neighbors for each node decreases by reducing the transmission range choice rate of each node. This is due to the fact that in such scenarios the nodes leverage a short transmission range.

All in all, to save the energy of nodes in the network it is very important that the sensors use suitable parameters. If we compare three figures (i.e. Fig. 5a, b, and c) with each other, it will become clear that networks have their best performance when their range choice rate is equal to 0.6. Therefore, we perform all simulations with 0.6 transmission range for each node from this point forward.

6.2. Average transmission range

The purpose of this experiment is to examine the average transmission range of network nodes for the protocols. In every node, the smaller the selected transmission range is (while it's connected to the network), the less energy is consumed, and, according to the reduction of the number of the neighbors, the conflict between nodes is also smaller.

In Fig. 6, the average transmission range of nodes for all protocols is seen in different network sizes. As it is seen, *LBLATC* protocol has less average transmission range than that of $RAA-2L$, $RAA-3L$, and *HOM*. But, in *CLATC* protocol this amount is approximately equal to that in *LBLATC*. Homogeneous (HOM) protocol has the maximum average transmission range, and for this reason, all nodes have R_t transmission range. $RAA-3L$ protocol has a less average transmission range than that of $RAA-2L$ protocol because, in $RAA-3L$, every node can choose its own transmission range among three transmission ranges, but, in $RAA-2L$ protocol, every node can choose its own transmission range between two transmission ranges.

6.3. Average number of neighbors

In this experiment, the average number of neighbors in network nodes has been experimented for the protocols. The gathered results from this experiment illustrated in Fig. 7 for the protocols under examination in different network sizes. As the number of neighbors has a direct influence on intermingling of nodes, having a lower transmission range has great impact, as it is evident, the proposed protocol has the least average number of neighbors compared to the other protocols. Therefore, the average number of neighbors is the most effective factor in network capacity.

6.4. Average residual energy

The average remaining energy of each node has been examined for all protocols. The results of this experiment are plotted in Fig. 8. It can be seen from Fig. 8 that the average remaining energy of network nodes, when determining the level of dissemination limit, is approximately

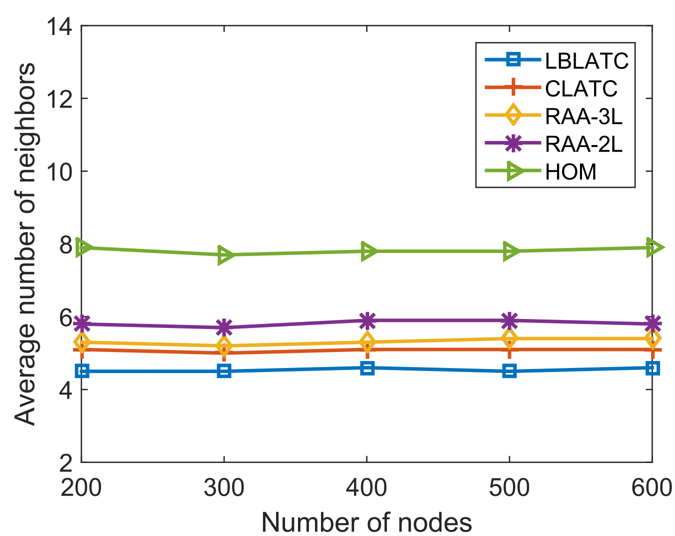


Fig. 7. Average range of neighbor degree of network nodes for LBLATC, CLATC,RAA-3L, RAA-2L, and HOM protocols in different network sizes.

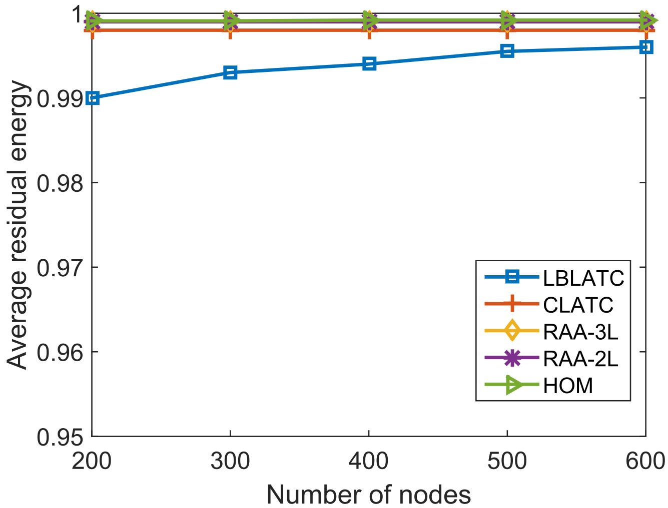


Fig. 8. Remaining energy of network's nodes for LBLATC, CLATC,RAA-3L, RAA-2L, and HOM protocols in different network sizes.

about its initial energy (1 J). In other words, although the consumed energy of *LBLATC* is more than that in *CLATC*, *HOM*, $RAA-2L$ and, $RAA-3L$ protocols (because of learning level fulfillment in this protocol), this consumed energy is very small in comparison with the total energy of each node (1 J). Our algorithm is an iterative algorithm which chooses the suitable topology over iterations. However, the overhead is negligible for long time network simulation. The remaining energy increases when the number of nodes increases. This is due to the fact that in dense networks there is a reduction in the transmission range of each to save the energy. According to this metric, the proposed protocol can maintain a suitable topology for the network without using much energy. It is worth stating that LBLATC maintains a suitable network topology by assigning a proper transmission range to each node and pruning the neighbor list. Leveraging a small number of neighbors with less transmission range results in better energy saving than other state-of-the-art works.

6.5. Network lifetime

In this section, we study network lifetime for various scenarios. First, we report the impact of transmission choice rate on the overall lifetime of the network for LBLATC protocol. Then, we report similar results for a network with various nodes for all protocols.

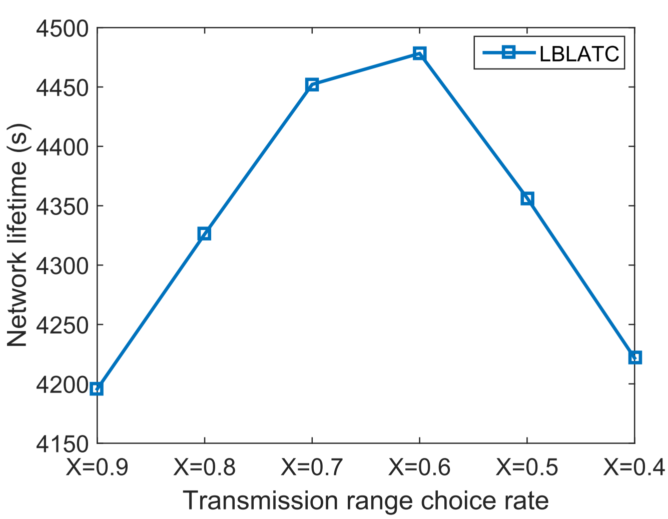


Fig. 9. Impact of transmission choice rate on network lifetime.

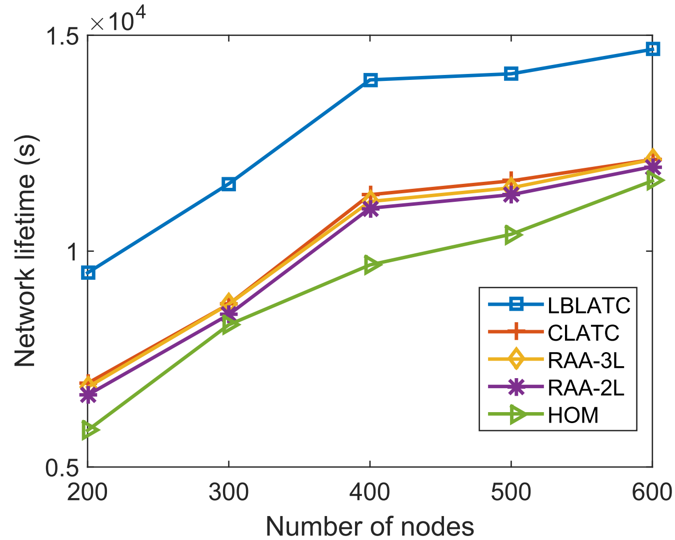


Fig. 10. Network lifetime for LBLATC, CLATC,RAA-3L, RAA-2L, and HOM protocols by varying the number of nodes.

Fig. 9 illustrates network lifetime for the scenario that the network has 200 nodes and the transmission choice rate varies between 0.9 and 0.4. The results report choosing the transmission range 0.6 gains much lifetime than other values. This result can be summarized as follows. Choosing 0.6 as transmission choice rate for each node in this scenario decreases the number of active neighbors for each node. Therefore, the nodes send less number of packets to neighbors which make the network more energy efficient.

We also compare the obtained network lifetime from all protocols. We perform this measurement based on the energy model in (Heinzelman et al., 2002) in which the data packet size is 100 bytes. We also assume that the packet rate is 1 packet/second. Fig. 10 depicts the LBLATC can gain more lifetime than other competitive algorithms. The rationale behind these results is that LBLATC leverages a short transmission range in sending the packets to neighbors which results in energy saving for nodes. Therefore, the obtained network lifetime by LBLATC is higher than other protocols.

7. Conclusion

Wireless sensor networks are widely exploited for surveillance systems such as battle-field monitoring. One of the critical concerns in such systems is to exploit the functionality of each node as long as possible. In this paper, a topology control protocol was proposed based on the learning automaton. It should be taken into account that, in the proposed protocol, the transmission range for every sensor is determined dynamically. In this protocol, nodes choose a suitable transmission range among their own transmission range with the aim of learning automaton. Learning automaton makes the nodes choose the smallest transmission range possible. Consequently, this choice has a determinant impact on overall lifetime of the network. Simulation results validate the performance of our proposed approach which has a better performance than competing algorithms in selecting a suitable transmission range for each individual node in the network. Mobility (Bouaziz and Rachedi, 2016) feature enables the nodes to move in the network region. This feature can help the nodes to improve the energy efficiency of the network. Developing an algorithm with mobility consideration can be a future direction.

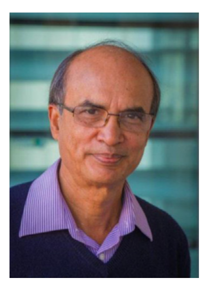
References

Abolhassani, S., Esnaashari, M., Meybodi, M., 2009. A cellular learning automata based topology control protocol for sensor networks. In: Proceedings of 14th Annual CSI Computer Conference of Iran. Amirkabir University of Technology, Tehran, Iran.

Akhtar, F., Rehmani, M.H., 2015. Energy replenishment using renewable and traditional energy resources for sustainable wireless sensor networks: a review. Renew. Sustain. Energy Rev. 45, 769–784.
Aziz, A.A., Sekercioglu, Y.A., Fitzpatrick, P., Ivanovich, M., 2013. A survey on distributed topology control techniques for extending the lifetime of battery powered wireless sensor networks. Commun. Surv. Tutorials, IEEE 15 (1), 121–144.
Blough, D.M., Leoncini, M., Resta, G., Santi, P., 2003. The k-neigh protocol for symmetric topology control in ad hoc networks. In: Proceedings of the 4th ACM International Symposium on Mobile Ad Hoc Networking & Computing. ACM, pp. 141–152.
Bouaziz, M., Rachedi, A., 2016. A survey on mobility management protocols in wireless sensor networks based on 6lowpan technology. Comput. Commun. 74, 3–15 current and Future Architectures, Protocols, and Services for the Internet of Things.
Deniz, F., Bagci, H., Korpeoglu, I., Yazıcı, A., 2016. An adaptive, energy-aware and distributed fault-tolerant topology-control algorithm for heterogeneous wireless sensor networks. Ad Hoc Netw. 44, 104–117.
Gubbi, J., Buyya, R., Marusic, S., Palaniswami, M., 2013. Internet of things (iot): a vision, architectural elements, and future directions. Future Generat. Comput. Syst. 29 (7), 1645–1660.
Guo, W., Zhang, B., Chen, G., Wang, X., Xiong, N., 2013. A pso-optimized minimum spanning tree-based topology control scheme for wireless sensor networks. Int. J. Distributed Sens. Netw. 2013.
Haque, I.T., Islam, M.S., Harms, J., 2015. On selecting a reliable topology in wireless sensor networks. In: 2015 IEEE International Conference on Communications (ICC). IEEE, pp. 6376–6382.
Heinzelman, W.B., Chandrakasan, A.P., Balakrishnan, H., 2002. An application-specific protocol architecture for wireless microsensor networks. Wirel. Commun. IEEE Trans. 1 (4), 660–670.
Jameii, S.M., Faez, K., Dehghan, M., 2016. Amof: adaptive multi-objective optimization framework for coverage and topology control in heterogeneous wireless sensor networks. Telecommun. Syst. 61 (3), 515–530.
Khalil, E.A., Ozdemir, S., Jun 2017. Reliable and energy efficient topology control in probabilistic wireless sensor networks via multi-objective optimization. J. Supercomput. 73 (6), 2632–2656.
Lee, C.-Y., Shiu, L.-C., Lin, F.-T., Yang, C.-S., 2013. Distributed topology control algorithm on broadcasting in wireless sensor network. J. Netw. Comput. Appl. 36 (4), 1186–1195.
Leu, J.-S., Chiang, T.-H., Yu, M.-C., Su, K.-W., 2015. Energy efficient clustering scheme for prolonging the lifetime of wireless sensor network with isolated nodes. IEEE Commun. Lett. 19 (2), 259–262.
Li, N., Hou, J.C., Sha, L., 2005. Design and analysis of an mst-based topology control algorithm. Wirel. Commun. IEEE Trans. 4 (3), 1195–1206.
Li, M., Li, Z., Vasilakos, A.V., 2013. A survey on topology control in wireless sensor networks: taxonomy, comparative study, and open issues. Proc. IEEE 101 (12), 2538–2557.
Lin, S., Miao, F., Zhang, J., Zhou, G., Gu, L., He, T., Stankovic, J.A., Son, S., Pappas, G.J., 2016. Atpc: adaptive transmission power control for wireless sensor networks. ACM Trans. Sens. Netw. 12 (1), 6.
Ma, J., Gao, M., Zhang, Q., Ni, L.M., 2007. Energy-efficient localized topology control algorithms in ieee 802.15. 4-based sensor networks. Parallel Distrib. Syst. IEEE Trans. 18 (5), 711–720.
Misra, S., Krishna, P.V., Kalaiselvan, K., Saritha, V., Obaidat, M.S., 2014. Learning automata-based qos framework for cloud iaas. Netw. Serv. Manag. IEEE Trans. 11 (1), 15–24.
Mostafaei, H., Menth, M., 2018. Software-defined wireless sensor networks: a survey. J. Netw. Comput. Appl. 119, 42–56.
Mostafaei, H., Chowdhury, M.U., Islam, R., Gholizadeh, H., 2015. Connected p-percent coverage in wireless sensor networks based on degree constraint dominating set approach. In: Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems, ser. MSWiM '15. ACM, New York, NY, USA, pp. 157–160.
Mostafaei, H., Montieri, A., Persico, V., Pescapé, A., 2017. A sleep scheduling approach based on learning automata for wsn partial coverage. J. Netw. Comput. Appl. 80, 67–78.
Narendra, K.S., Thathachar, M.A.L., 1989. Learning Automata: an Introduction. Prentice Hall.
Pantazis, N.A., Nikolidakis, S.A., Vergados, D.D., 2013. Energy-efficient routing protocols in wireless sensor networks: a survey. IEEE Commun. Surv. Tutorials 15 (2), 551–591.
Qureshi, H.K., Rizvi, S., Saleem, M., Khayam, S.A., Rakocevic, V., Rajarajan, M., 2013. Evaluation and improvement of cds-based topology control for wireless sensor networks. Wireless Network 19 (1), 31–46.
Santi, P., 2005. Topology control in wireless ad hoc and sensor networks. ACM Comput. Surv. 37 (2), 164–194.
Stauffer, D., Aharony, A., 1994. Introduction To percolation Theory. CRC press.
Torkestani, J.A., 2013. An energy-efficient topology construction algorithm for wireless sensor networks. Comput. Network. 57 (7), 1714–1725.
Wattenhofer, R., Zollinger, A., 2004. Xtc: a practical topology control algorithm for ad-hoc networks. In: Parallel and Distributed Processing Symposium, 2004. Proceedings. 18th International. IEEE, p. 216.
Yang, K., 2014. "Wireless Sensor Networks," Principles, Design and Applications.
Zhang, X.M., Zhang, Y., Yan, F., Vasilakos, A.V., 2015. Interference-based topology control algorithm for delay-constrained mobile ad hoc networks. IEEE Trans. Mobile Comput. 14 (4), 742–754.
Zhang, B., Jiao, Z., Li, C., Yao, Z., Vasilakos, A.V., 2016. Efficient location-based topology control algorithms for wireless ad hoc and sensor networks. Wireless Commun. Mobile Comput. 16 (14), 1943–1955.
Wireless Sensor Networks Simulator, Aug. 2017. http://www.djstein.com/Projects/Files/Wireless%20Sensor%20Network% 20Simulator%20v1.1.zip.

Mahmood Javadi is a PhD student at the department of computer engineering of Islamic Azad University. He received the M.S. degree from the Islamic Azad University Arak branch, in 2009 and the B.S. degree from the Islamic Azad University Khoy branch, in 2006, both in software engineering. His research interests include wireless networks, Computer Networks, and cloud computing.

Habib Mostafaei is currently pursuing the PhD degree at the department of engineering of Roma Tre University, Italy. He is also a visiting researcher at the Department of Computer Science at the University of Tuebingen/Germany. He received the M.S. degree in software engineering from the Islamic Azad University, Arak branch in 2009. Prior to the PhD training at Roma Tre University, he was a lecturer at the Computer Engineering Department of Islamic Azad University (2009–2015). He has served as a reviewer for a number of journal and conference papers and he is awarded as an outstanding reviewer for Elsevier Journal of Networks and Computer Applications (JNCA) in October 2016 and for Journal of Computational Science in April 2017. His research interests include Software Defined Networking (SDN), Interdomain routing, and wireless networks.



Morshed U. Chowdhury received his Ph.D. degree in Computing from Monash University, Australia in 1999. He is an academic staff in the School of Information Technology, Deakin University, Burwood, Australia. He has more than 12 years of industry experiences and has published more than 162 refereed articles. He has organized a number of international conferences and served as a member of program committees of several international conferences. He supervised numerous Ph.D. students to completion and is on the editorial boards of couple of journals.

JEMAL H. ABAWAJY is a Professor at the School of Information Technology, Deakin University, Australia. He is a senior member of IEEE and leads the Parallel and Distributed Computing Lab at Deakin University. Professor Abawajy is actively involved in funded research and has published more than 200 articles in refereed journals, conferences and book chapters. He is currently principal supervisor of 10 PhD and co-supervisor of 3 PhD students. Professor Abawajy is on the editorial member of several journals and has guest-edited several journals. Professor Abawajy has been a member of the organizing committee for over 100 international conferences serving in various capacity including chair, general co-chair, vice-chair, best paper award chair, publication chair, session chair and program committee.