Wireless Netw
DOI 10.1007/s11276-015-1061-6

An ant colony optimization based routing algorithm for extending network lifetime in wireless sensor networks

Abdolreza Mohajerani[1] · Davood Gharavian[1]

Abstract Reducing the energy consumption of network nodes is one of the most important problems for routing in wireless sensor networks because of the battery limitation in each sensor. This paper presents a new ant colony optimization based routing algorithm that uses special parameters in its competency function for reducing energy consumption of network nodes. In this new proposed algorithm called life time aware routing algorithm for wireless sensor networks (LTAWSN), a new pheromone update operator was designed to integrate energy consumption and hops into routing choice. Finally, with the results of the multiple simulations we were able to show that LTAWSN, in comparison with the previous ant colony based routing algorithm, energy aware ant colony routing algorithms for the routing of wireless sensor networks, ant colony optimization-based location-aware routing algorithm for wireless sensor networks and traditional ant colony algorithm, increase the efficiency of the system, obtains more balanced transmission among the nodes and reduce the energy consumption of the routing and extends the network lifetime.

Keywords Wireless sensor networks · Routing algorithms · Ant colony optimization · Energy consumption · Network lifetime

✉ Davood Gharavian
dgharavian@gmail.com; d_gharavian@sbu.ac.ir

Abdolreza Mohajerani
mabdoreza@gmail.com

[1] Faculty of Electrical Engineering, Shahid Beheshti University, Tehran, Iran

1 Introduction

A wireless sensor network (WSN) typically consists of tens to hundreds or thousands of relatively small nodes, each equipped with a sensing device. Most sensor networks use wireless communication, and the nodes are often battery powered. Their limited resources, restricted communication capabilities, and constrained power consumption demand that efficiency be high on the list of design criteria [1]. As a result of the advances in wireless communication and electronics technologies, wireless sensors are getting smaller, cheaper, and more powerful. Due to the fast development of the microprocessor, sensor and transceiver, there is great applications foreground about WSNs. Also since we often use these networks in rough and inaccessible environments such as battlefields, volcanoes, forests and so on, normally there is low possibility to change or recharge the defective or dead nodes. Hence, the main difference between WSNs and other classic wireless networks is that WSNs are hypersensitive and vulnerable to energy [2].

The limit energy is the key issue influencing WSNs performance. So, how to use the limit energy of WSNs to maximize the life of WSNs becomes the all-important problem of routing design [3]. Most of the routing algorithms for sensor networks require location information for sensor nodes. In most cases location information is needed in order to calculate the distance between two particular nodes so that energy consumption can be estimated [4]. Therefore, location information can be utilized in routing data in energy efficient way.

A family of ant colony optimization (ACO) algorithms has been successfully applied to solve some routing problems in WSN [5]. Over the last two decades, ant colony optimization has emerged as a leading Meta heuristic

Published online: 14 November 2015

method for the solution of combinatorial optimization problems [4].

In this paper, we proposed a routing algorithm for wireless sensor network based on ant colony optimization with special parameters. The main objective of the algorithm is to maximize the network lifetime by carefully defining link cost as a function of node remaining energy and the required transmission energy using that link. We call the proposed algorithm as life time aware routing algorithm for wireless sensor networks (LTAWSN) and compare it with energy aware ant colony routing algorithms for the routing of wireless sensor networks (EAACA) that presented in [6], ant colony optimization-based location-aware routing algorithm for wireless sensor networks (ACLR) that presented in [5, 7], and traditional ant colony routing algorithm ACA, and see that proposed algorithm reduce consumption of energy in comparison of these routing algorithms, obtains more balanced transmission among the node, therefore extends the network lifetime.

The rest of this paper is organized as follows. In Sect. 2, some of the recent researches about ant colony routing algorithm in wireless sensor networks are presented. In Sect. 3, the proposed approach is described. Section 3 represents the simulation parameters. Section 4 discusses about the simulation results and finally Sect. 5 concludes the paper.

2 Related work

Some of the recent researches about ant colony routing algorithm in wireless sensor networks are presented as follows:

The authors in [5] proposed a routing algorithm for wireless sensor networks using ant colony optimization that present a comparison of two ant colony-based routing algorithms, taking into account current amounts of energy consumption under different scenarios and reporting the usual metrics for routing in wireless sensor networks.

In [6], the authors proposed an energy aware ant colony algorithm for the routing of wireless sensor networks that when the ant chooses the next node, not only the distance of sink node, but also the residual energy of next node and the path of the average energy are taken into account. This algorithm was compared with traditional ACA algorithm and gets more improvement in balance the energy consumption of nodes and extends the network life time.

In [8], the authors proposed a fair comparison of low energy adaptive clustering hierarchy (LEACH) and ant colony applied on LEACH on the basis of the death of first node in the wireless sensor networks and is shown that when the ant colony algorithm is applied on existing LEACH protocol, the network lifetime has improved.

In [9] first, a grade table is build and referred to generate several possible routing paths. Then the ACO explores these paths to reduce the power consumption of the nodes.

In [10] each node calculates the amount of its own energy level and then sums up the energy level of the remaining network. With the help of this comparison the node decides whether to become the cluster head or not for that round. The nodes with higher energy are more likely to become cluster heads. The drawback of this approach is that it requires extra communication of nodes with base station which in turn needs more energy.

In [11] the authors proposed an energy-efficient ant-based routing algorithm (EEABR) for flat and location awareness architectures. In this proposal, the ants look for less energy consuming path meanwhile reducing the size of the ants during the communication among nodes.

In [7] the authors proposed the called ant colony optimization-based location-aware routing algorithm (ACLR) which is a flat and location awareness algorithm. It fuses the residual energy and the global and local location information of nodes, to define the probability to select the next node for the ants.

In [12] the authors proposed an ant colony optimization algorithm and apply it to energy control and congestion control on wireless sensor network route. In this algorithm, the pheromone and the energy of the node are combined to affect the pheromone consent ration in optimization path, which can avoid network congestion and fast consume of energy of individual node. Then it can prolong the lifecycle of the whole network.

The authors in [13] are proposed a predication mode routing algorithm based on ACO (PRACO) to achieve the energy-aware data-gathering routing structure in wireless sensor networks. This algorithm checks the load factor in heuristic factor and proposes a novel pheromone updating rule. In this algorithm artificial ants can foresee the local energy state of networks and the corresponding actions could be adaptively taken to enhance the energy efficiency in routing construction.

The authors in [14] proposed a new energy efficient routing algorithm for wireless sensor networks consisting routing and clustering phases. The simulation results showed that this algorithm in comparison of other algorithms extends network lifetime and reduce energy consumption. However, in this paper the dynamic scenario and fault tolerant aspects of the sensor network had not considered by the authors.

A particle swarm optimization based routing algorithm which maximizes the lifetime of the wireless sensor networks is represented in [15]. The main idea of this approach is minimizing the energy consumption of gateways near to the base station and distributing the routing load over them. The proposed approach are compared with two other algorithm based on number of dead sensor nodes, standard deviation of remaining energy of cluster heads and number of data packets received by the base station.

A cluster based approach for extending the network lifetime is proposed in [16]. In this paper also new coverage importance cost metrics *CI* for different application coverage problems are introduced. The simulation results are shown that this approach compared with previous protocols can construct a reasonable clustering network topology with lower energy consumption and better coverage performance that extend the network lifetime.

"The authors in their paper [17] propose a method based on a hybrid genetic algorithm and aims to accomplish the establishment of a maximal number of connections with the minimal number of isochronous channels. The authors in [18] present a comprehensive list of major known security threats within a cognitive radio network (CRN) framework.

The authors in [19] provide an overview of topology control techniques. In their work existing topology control techniques is classified into two categories: network coverage and network connectivity. The possibility of exploiting partially overlapped channels (POCs) by introducing a novel game theoretic distributed CA algorithm is explored in [20]. The proposed algorithm in this paper outperforms both the conventional orthogonal channel approach and the recent heuristic CA algorithms using POC.

A novel QoE-driven channel allocation scheme for SUs and cognitive radio networks (CRN) base station (BS) is proposed in [21]. In this paper, the historical QoE data under different primary channels (PCs) are collected by the SUs and delivered to a Cognitive Radio Base Station (CRBS). The authors in [22] propose a survey aiming at revealing insights into the following three key questions: First, what are the meaningful algorithm design problems for DC-WSNs? Second, which problems have been studied and which have not? And finally, what are the essential techniques behind the existing solutions?

The authors in [23] survey the state-of-the-art routing metrics for cognitive radio networks. They start by listing the challenges that have to be addressed in designing a good routing metric for cognitive radio networks. The authors in [24] investigate the fundamental performance limits of medium access control (MAC) protocols for particular multi-hop, RF-based wireless sensor networks and underwater sensor networks.

To combat against attacks on encrypted protocols, the authors in [25] propose an anomaly-based detection system by using strategically distributed monitoring stubs (MSs). The proposed approach focuses on both Detection and trace back in the MS level. A novel compressive data collection scheme for wireless sensor networks is proposed in [26]. The authors adopt a power-law decaying data model verified by real data sets and then propose a random projection based estimation algorithm for this data model. An online, multi-objective optimization (MO) algorithm to efficiently schedule the nodes of a wireless sensor network (WSN) and to achieve maximum lifetime is proposed in [27].

The authors in [28] propose MAPCloud as a hybrid, tiered cloud architecture consisting of local and public clouds. They show how it can be leveraged to increase both performance and scalability of mobile applications. The authors in [29] propose the use of a computational intelligence approach—a reinforcement learning algorithm (RLA)—for optimizing the routing in asynchronous transfer mode (ATM) networks based on the *private network-to-network interface* (PNNI) standard. A cellular computing model in the slime mold physarum polycephalum is proposed in [30] to solve the *Steiner tree problem* which is an important NP-hard problem in various applications, especially in network design.

The authors in [31] argue that by carefully considering spatial reusability of the wireless communication media, onw can tremendously improve the end-to-end throughput in multi-hop wireless networks. The authors in [32] present an overview of body area networks, and a discussion of BAN communications types and their related issues. They also provide a detailed investigation of sensor devices, physical layer, data link layer, and radio technology aspects of BAN research.

The authors in [33] study the properties of trust, propose objectives of IoT trust management, and provide a survey on the current literature advances towards trustworthy IoT. A new approach to the design of S-model ergodic reinforcement learning algorithms is introduced in [34].The authors in [35] propose a directional routing and scheduling scheme (DRSS) for green vehicle DTNs by using Nash Q-learning approach that can optimize the energy efficiency with the considerations of congestion, buffer and delay.

The paper [36] is analyzed the security problems of three layers of IoT containing perception layer, transportation layer and application layer, separately. The authors in [37] consider the assignment strategy with topology preservation by organizing the mesh nodes with available channels, and aim at minimizing the co-channel interference in the network. A novel prediction-based data collection protocol is proposed in [38], in which a double-queue mechanism is designed to synchronize the prediction data series of the sensor node and the sink node, and therefore, the cumulative error of continuous predictions is reduced.

A multi-constrained QoS multicast routing method using the genetic algorithm using the available resources and minimum computation time in a dynamic environment is proposed in [39].The study presented in [40] propose a novel vehicular clustering scheme integrating hierarchical clustering on the basis of classical routing algorithm. Simulation results show that the new scheme efficiently mitigates the hot spot problem in WSN and achieves much improvement in network lifetime and load balance compared to the old algorithm which is Direct, LEACH and DCHS. The authors in [41] exploits a biological model of physarum to design a novel biology-inspired optimization algorithm for MEP.

A reliable multicast protocol, called CodePipe, with energy-efficiency, high throughput and fairness in lossy wireless networks is proposed in [42].The notion of multi-objective path selection in mobile ad hoc networks (MANET) using an evolutionary fuzzy cost function to deliberately compute cost adaptively is described in [43].A reliable multicast protocol, called CodePipe, with advanced performance in terms of energy-efficiency, throughput and fairness in lossy wireless networks is proposed in [44].The work in [45] stems from the insight that, recent research efforts on open vehicle routing (OVR) problems, an active area in operations research, are based on similar assumptions and constraints compared to sensor networks.

The article [46] presents an overview of current standards and research activities in internet of things (IoT) field in both industry and academia. The authors in [47] investigate the application of compressed sensing (CS) to data collection in wireless sensor networks aiming at minimizing the network energy consumption through joint routing and compressed aggregation. The authors in [45] proposed both a centralized heuristic to reduce its computational overhead and a distributed heuristic to make the algorithm scalable for large-scale network operations. They also develop EDAL to be closely integrated with compressive sensing, an emerging technique that promises considerable reduction in total traffic cost for collecting sensor readings under loose delay bounds.

Various remarkable techniques toward green mobile networks are listed in [48]. The authors mainly target mobile cellular networks in their article. The authors in [49] exploit cross-layer optimization techniques that extend dynamic source routing (DSR) to improve its routing energy efficiency by minimizing the frequency of recomputed routes. The authors in [50] study the routing games in general networks where each player selfishly selects a path that minimizes the sum of congestion and dilation of the player's path. In article [51], a novel hierarchical data aggregation method using compressive sensing (HDACS) is presented, which combines a hierarchical network configuration with compressive sensing (CS).

The authors in [52] consider an alternative, highly agile approach called backpressure routing for delay tolerant networks (DTN), in which routing and forwarding decisions are made on a per-packet basis. Finally, in [53], the protocols and application of delay tolerant networks is discussed."

Compared with presented works in this area, the proposed method in this paper uses two energy parameters in its competency function. The first competency function captures the remaining energy levels of neighborhood nodes in next-hop selection process, while the second one focuses on the consumed amount of energy in each neighborhood node. Since, the proposed ant colony optimization based algorithm takes more attention to energy parameters leading to prolonging the lifetime of the network.

3 The proposed ACO based routing algorithm (LTAWSN)

In this section, we want to propose the idea behind LTAWSN algorithm. First, a traditional ant colony optimization based routing algorithm for WSNs is presented. Next, EAACA algorithm is presented. Finally, the LTAWSN routing algorithm is proposed that tries to provide further improvements in energy consumption and extends the network lifetime.

3.1 Basic ACO based routing for WSNs (ACA)

Wireless sensor networks (WSN) can be represented by a weighted undirected connectivity-graph G (V, E).Where V is the set of sensor nodes and E is the set of links between these nodes. Any node in WSN area has a set of neighbors that are placed in wireless communication coverage of the node. We use the Euclidean distance for calculate the distance between two node in WSN area. The Euclidean distance between i and j, is calculated by:

$$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{1}$$

where $i = (x_i, y_i), j = (x_j, y_j)$.

Ant-based routing algorithm use ant-like control packets to discover routes between pairs of nodes and to optimize existing routing information. These ants are query packets that try to establish all valid paths from source node to the destination node. The algorithm assumes that the sensor network has only a single sensor destination and makes use of two kinds of ants, forward ants that travel from the source node to the destination node, exploring new paths and gathering information, and backward ants, that travel back to the sources from the destination to update the information in each sensor node as they move [5, 6, 12, 13, 54, 55]. They do this work with release pheromone to established path. Pheromone values determine how ants originating at a source node, and bound for a destination node will move from one node to the next along a multi hop path. In each travels each of forward ants must select next-hop node from neighbor candidate list to establish its paths. The neighbor candidate list for each node is comprised of nodes that are placed in wireless communication coverage of the node. The probability of an ant moving from any current node i to another one j in traditional ACO based routing algorithm is given by [5, 7, 55]:

$$P_{ij}^{k}(t) = \frac{[\psi_{ij}(t)]^{\alpha} \times [\varepsilon_{ij}(t)]^{\beta}}{\sum_{s_l \in C(s_i)} [\psi_{il}(t)]^{\alpha} \times [\varepsilon_{il}(t)]^{\beta}}. \tag{2}$$

where $P_{ij}^{k}(t)$ is the transfer packet probability of node i to another one j for ant k in time t, $\psi_{ij}(t)$ is the density of pheromone accumulated on the path segment i and j by ants in time, $\varepsilon_{ij}(t)$ is the information of searching for that path segment, and α, β are the two constant exponents associated with the algorithm. The location function, $\varepsilon_{ij}(t)$ proposed by traditional routing algorithm is defined as follows [5, 7, 55]:

$$\varepsilon_{ij} = \frac{1}{d_{ij}} \tag{3}$$

where d_{ij} is the Euclidean distance between node i and node j. If the ant finds the destination node, a path between source node and destination node is established. Then the destination node generates a response packet (backward ant). The backward ant goes back to the sending node along the reverse path, and release pheromone while it returns. The pheromone $\psi_{ij}(t)$, will be update at the end of each searching period in the way of [5, 7, 55]:

$$\psi_{ij}(t+1) = (1-\rho) \times \psi_{ij}(t) + \Delta\psi_{ij}(t). \tag{4}$$

where ρ is the pheromone evaporation factor, and $\rho \in (0,1)$, and $\Delta\psi_{ij}(t)$, is the pheromone increment on the route between node i and node j in the current round travel, That is sum of released pheromone by ant k in wireless link between node i and node j:

$$\Delta\psi_{ij} = \sum_{k=1}^{n} \Delta\psi_{ij}^{k} \tag{5}$$

$\Delta\psi_{ij}^{k}$ in the traditional algorithm, if ant k choose (i, j) is defined as follows [5, 7, 55]:

$$\Delta\psi_{ij}^{k} = \frac{A}{L^{k}}. \tag{6}$$

where L^{k} is the length of path founded by ant k and A is a constant. This algorithm repeats until certain number of iteration for certain number of ants. This loop performed until algorithm reaches a certain number of iterations for certain number of ants.

3.2 An energy aware ant colony algorithm for routing of wireless sensor networks (EAACA)

In EAACA [6], for calculating the packet transfer probability to the next hop neighbor, the residual energy of node is considered. Ants are launched from a source node and move towards destination node, hopping from one node to the next. Ant k in node i choose the next node j to move to, according to a probabilistic decision rule:

$$P_{ij}^{k}(t) = \frac{[\psi_{ij}(t)]^{\alpha} \times [\mu_{ij}(t)]^{\beta}}{\sum_{s_l \in C(i)} [\psi_{il}(t)]^{\alpha} \times [\mu_{il}(t)]^{\beta}}. \tag{7}$$

where$P_{ij}^{k}(t)$, $\psi_{ij}(t)$ are transfer packet probability and pheromone metric, respectively. $\eta_{ij}(t)$ is the energy function proposed by EAACA and is defined as follows:

$$\mu_{ij} = \frac{1}{E - e_j(t)} \tag{8}$$

where E is the initial energy of nodes and $e_j(t)$ is the actual energy of node j in time t.

In EAACA, the pheromone $\psi_{ij}(t)$, will be update at the end of each searching period in the way of [6]:

$$\psi_{ij}(t+1) = (1-\rho) \times \psi_{ij}(t) + \frac{\Delta\psi_{ij}(t)}{\omega.hop_{count_k}} \tag{9}$$

where hop_{count_k} represents the number of nodes that ant k visited them in network from source node to destination node that is equal to L^{k} in traditional algorithm and ω is a constant.

EAACA, not only considers the distance of paths, but also consider the energy level of paths [6]; so, the pheromone concentration is improved as follow [6]:

$$\Delta\psi_{ij} = c \times (hop_{\max} - hop_{count_k}) \times E_{avg_k}. \tag{10}$$

where $hop_{\max}$ represents the maximum allowed number of hops for ants in network, hop_{count_k} represents the number of hops for ant k in network from source node to destination node (the number of nodes visited by ant k), c is a constant and E_{avg_k} is average energy of nodes that ant k is visited them.

In EAACA algorithm, is assumed that, the concentration of pheromone cannot be reducing to zero or negative value and pheromone become no lower than default value [6]. During the process of finding path to destination node, default value of pheromone ensures that every neighbor could be the next node [6].

3.3 An ant colony optimization based routing algorithm for extends network lifetime in wireless sensor networks (LTAWSN)

In this section, we propose an ant colony based routing algorithm with special parameters in competency function that try to reduce energy consumption of network nodes and also obtains more balanced transmission among the node and prolong the network lifetime. Low energy consumption and long lifetime are the most basic conditions for good performance of WSNs. Therefore, it is very necessary to put the factor of energy consumption into routing design.

In our schemes we aim at building a system that would ensure that total energy dissipation is divided equally among all the nodes of the network. In order to optimize of the routing quality and the energy consumption, it is need to achieve the tradeoff between route hops and the energy consumption.

In LTAWSN algorithm, the neighbor candidate list for each node is comprised of nodes that are placed in wireless communication coverage of the node and also are nearer to destination node in comparison of current node.

Since energy metric is one of the important parameter in competency function, we use two energy metrics in this function that each of them has owns definition. At the other hands, based on this fact that the nearer node to destination node in neighbor candidate list for each current node, with higher probability, can reach to destination node with lower number of hops, we consider a spatial parameter in probability function of LTAWSN algorithm. This parameter considers distance of candidate list nodes to destination node and nodes that are nearer to destination node, with higher probability are selected. The probability function of LTAWSN algorithm for choice of the next-hop node in current travel is made to this probabilistic decision rule:

$$P_{ij}^{k}(t) = \frac{[\psi_{ij}(t)]^{\alpha} \times [\eta_{ij}(t)]^{\beta} \times [\eta'_{ij}(t)]^{\gamma} \times [\varepsilon_{ij}(t)]^{\delta}}{\sum_{s_l \in C(i)} [\psi_{il}(t)]^{\alpha} \times [\eta_{il}(t)]^{\beta} \times [\eta'_{il}(t)]^{\beta} \times [\varepsilon_{il}(t)]^{\delta}}. \tag{11}$$

where $P_{ij}^{k}(t)$, $\psi_{ij}(t)$ are transfer packet probability and pheromone metric, respectively, $\alpha, \beta, \gamma, \delta$ are the control parameters and $\eta_{ij}(t)$ is the first energy metric that has the following definition:

$$\eta_{ij}(t) = \frac{e_j(t)}{\sum_{s_l \in C(i)} e_l(t)} \tag{12}$$

This equation cause that the node with higher energy level in candidate list, has higher probability to selection. $\eta'_{ij}(t)$ is the second energy metric that defines as follow:

$$\eta'_{ij}(t) = \frac{\left(E - e_j(t)\right)^{-1}}{\sum_{j \in C(i)} \left(E - e_j(t)\right)^{-1}} \tag{13}$$

the distance between node consumption of energy in candidate list, has higher probability to selection. These two parameters in competency function of LTAWSN algorithm ensure that total energy dissipation is divided equally among all the nodes of the network.

In most routing algorithms location information is needed in order to calculate the distance between two particular nodes so that energy consumption can be estimated. Therefore, location information can be utilized in routing data in an energy efficient way. The location function proposed in LTAWSN, ε_{ij} is defined by:

$$\varepsilon_{ij} = \frac{d_{jd}}{\sum_{s_l \in C(i)} d_{ld}}. \tag{14}$$

where d_{jd} is the distance between node j (that is in candidate list of node i) and destination node d. This equation cause that the nearer node to destination node in neighbor candidate list, has higher probability for selection as a next-hop node in current travel.

If there is not any next-hop neighbor to select, then ant k returns to the previous-hop node and that node is added to the contraindication list of the ant k.

After all ants have completed their tour, each ant deposits a quantity of pheromone given in this equation:

$$\Delta\psi_{ij}^{k} = \frac{(hop_{\max} - hop_{count_k} + \upsilon)^{1.5} \times E_{avg_k}}{hop_{count_k}}. \tag{15}$$

where $hop_{\max}$, hop_{count_k} and E_{avg_k} have the same meaning as that of (10). The amount of pheromone on each connection of the nodes in LTAWSN algorithm is defined as (4).

In this algorithm, we also assume that, the concentration of pheromone cannot be reducing to zero or negative value and pheromone become no lower than default value.

After definition of design issue of proposed algorithm, LTAWSN algorithm is defined as follow:

Algorithm 1. (LTAWSN algorithm)

1. **Start**
2. **Initialize** the network size $m \times n$ and number of sensor nodes, number of ants and number of iterations; distribute nodes uniformly in this area
3. **Initialize** the default pheromone level of links between network nodes and also the energy level of each node;
4. A set of ants placed in source node
5. **for** (i=1 **to** iteration number **)**
6. **begin**
7. **for** (j=1 **to** ant number)
8. **begin**
9. Cnode (Current node) = source node
10. **while** Cnode!= destination node
11. **Begin**
12. **Calculate** energies and location metrics between current node and its neighbors in its candidate list according to formula (12), (13), (14).
13. Consider pheromone level between current node and its neighbors in its candidate list
14. **Calculate** $P_{ij}^{k}(t)$ probability function for nodes in candidate list of Cnode according to formula (11)
15. **Choose** the next-hop node
16. Cnode= next-hop node
17. **End while**
18. **End for**
19. Modify the path density of pheromone according to formula (15)
20. **End for**
21. **End**

Table 1 Simulation parameters for the network with size of 100 × 100 m^2

Parameter	Values
Network size	100 × 100 m^2
R	20 m
Number of nodes	125–300
Ant number	20
ρ	0.8
$\psi_{ij}(0)$	0.01
E	1 J
Et	4.28 µJ/bit
Er	2.36 µJ/bit
MAC layer protocol	IEEE 802.11

4 Simulation results

For all algorithms WSN nodes are deployed in certain area uniformly. The parameters used in stimulation, are shown in Table 1. In this table, R is the wireless communication radius of sensors, ρ is pheromone evaporation rate, $\psi_{ij}(0)$ is the initial pheromone level for every pair of adjacent nodes, E is the initial energy of nodes, Et is the energy consumption per bit transmitted and Er is the energy consumption per bit received. On the assumption that, m sensor nodes are randomly laid in the monitor area of the simulation model and the value of m is among 125–300, analyses of simulation results.

The parameters values of ACA algorithm is: $\alpha = 1, \beta = 1$, ACLR is: $\alpha = 1, \beta = 1, \gamma = 1$. The parameters values of EAACA algorithm established as follow: $\alpha = 1.5, \beta = 1.5$ and parameters values of the proposed algorithm established as follow: $\alpha = 1.5, \beta = 1.5, \gamma = 1.5, \delta = 2, \vartheta = 0.001$.

The simulation mainly compares new proposed routing algorithm LTAWSN, with the EAACA routing algorithm, ACLR routing algorithm and traditional ACO routing ACA in the average energy consumption of the network.

The average energy consumption metric refers to the total used energy in the network in the progress of finding the optimal route from the source node to the destination node. To be fair in the comparison, we use the energy consumption per bit that is shown in [56], for the transmitting and receiving data in each node.

Average energy consumption is the basic standards to measure the merits of routing algorithms [5]. The result of energy consumption for independent experiments of these algorithms, that each performs on networks with different nodes is shown in Fig. 1. The lifetime of these networks are shown in Fig. 2.

To show validity of the proposed algorithm, two simulations with different network size are presented. The result of energy consumption for the network with another topology (size of 200 × 200) is represented in Fig. 3. Also, Fig. 4 depicts the result of energy consumption for another network size (size of 500 × 500) and topology. The parameters used in these two simulations are shown in Tables 2 and 3 respectively.As represented in Fig. 3, in this simulation the number of nodes has varied from 200 to 400 nodes. In Fig. 4, the number of nodes is considered from 330 to 550 nodes. The simulation results indicate that average energy consumption is reduced in the proposed method. Simulation results indicate that the proposed method has the best performance in all investigated topologies. It can be seen that the average energy consumption of nodes in proposed algorithm is lower than that of EAACA, ACLR and ACA algorithms. The energy consumption of the network is saved to extend the network lifetime. Therefore, proposed algorithm makes the network live longer and has higher reliability.

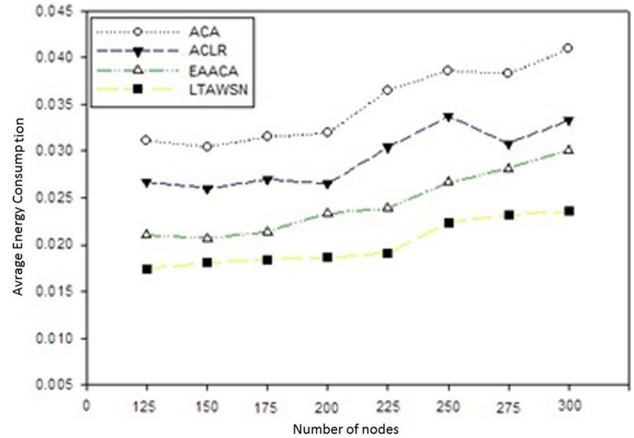

Fig. 1 Average energy consumption for the network with size of 100 × 100 m^2

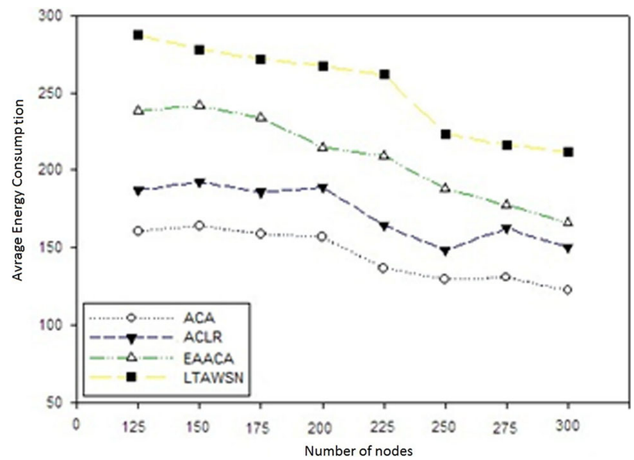

Fig. 2 Network lifetime for the network with size of 100 × 100 m^2

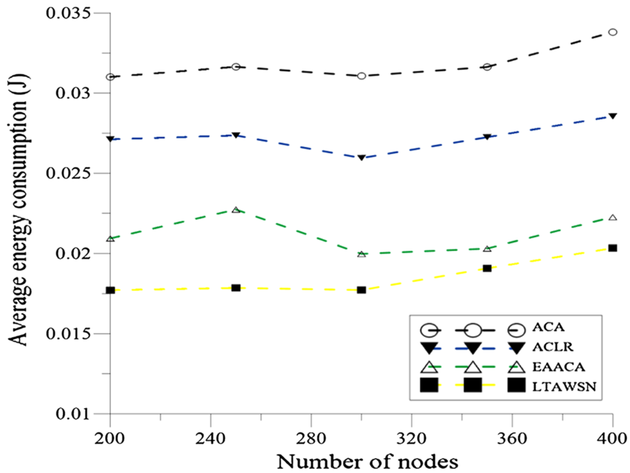

Fig. 3 Average energy consumption for the network with size of 200 × 200 m^2

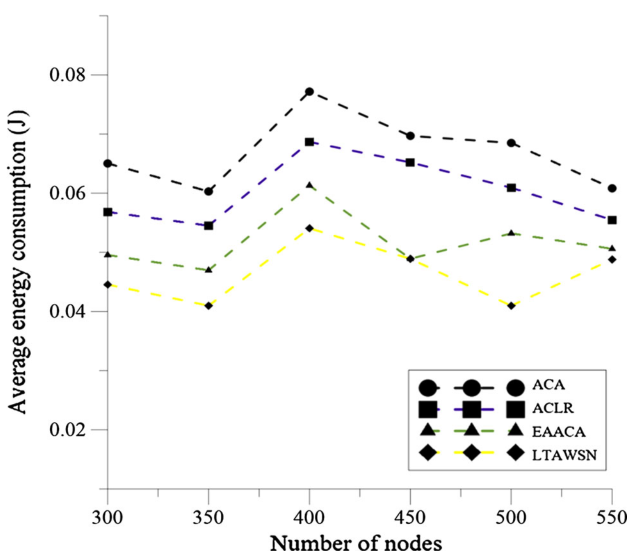

Fig. 4 Average energy consumption for the network with size of 500 × 500 m^2

Table 2 Simulation parameters for the network with size of 200 × 200 m^2

Parameter	Values
Network size	200 × 200 m^2
R	40 m
Number of nodes	125–300
Ant number	20
ρ	0.8
$\psi_{ij}(0)$	0.01
E	1 J
Et	4.28 μJ/bit
Er	2.36 μJ/bit
MAC layer protocol	IEEE 802.11

Table 3 Simulation parameters for the network with size of 500 × 500 m^2

Parameter	Values
Network size	500 × 500 m^2
R	50 m
Number of nodes	125–300
Ant number	20
ρ	0.8
$\psi_{ij}(0)$	0.01
E	1 J
Et	4.28 μJ/bit
Er	2.36 μJ/bit
MAC layer protocol	IEEE 802.11

5 Conclusion

In this paper, we propose a new ACO based routing algorithm that use spatial parameters in its competency function and a new pheromone update operator was designed to integrate energy consumption and hops into routing choice. In our schemes we aim to build a system that would ensure that total energy dissipation is divided equally among all the nodes of the network. The results are shown that this new proposed algorithm in comparison of EAACA, ACLR and ACA routing ACO based algorithm obtains more balanced transmission among the node, also can reduce the energy consumption of the routing and, therefore extends the network lifetime and increase the system efficiency.

References

1. Tanenbaum, A. S., Van Steen, M. (2006). *Distributed system principles and paradigm*, second edition.
2. Enami, N., Askari Moghadam, R., & Haghighat, A. T. (2010). A survey on application of neural networks in energy conservation of wireless sensor networks. In *WiMo 2010, CCIS 84* (pp. 283–294). Heidelberg: Springer.
3. Jiang, X, & Hong, B. (2010). ACO based energy-balance routing algorithms for WSNs. In *LNCS-6145* (pp. 298–305). Heidelberg: Springer.
4. Akkaya, K., Younis, M. (2003). A survey on routing protocols for wireless sensor networks.
5. Medina, C. D., & Cortes, N. C. (2010). Routing algorithms for wireless sensor networks using ant colony optimization. In *MICAI 2010, part II, LNAL-6438* (pp. 337–348). Heidelberg: Springer.
6. Cheng, D., Xun, Y., Zhou, T., & Li, W. (2011). An energy aware ant colony routing algorithms for the routing of wireless sensor networks. In *ICICIS 2011, part I, CCIS-134* (pp. 395–401). Heidelberg: Springer.
7. Wang, X., Li, Q., Xiong, N., & Pan, Y. (2008). Ant colony optimization-based location-aware routing for wireless sensor

networks. In Y. Li, D. T. Huynh, S. K. Das, & D. Z. Du (Eds.), *WASA 2008* (Vol. 5258, pp. 109–120)., LNCS Heidelberg: Springer.
8. Agarwal, T, Kumar, D., & Prakash, N. R. (2010). Prolonging network lifetime using ant colony optimization algorithm on LEACH protocol for wireless sensor networks. In *NewCom, WiMon, WeST 2010, CCIS-90* (pp. 634–641). Heidelberg: Springer.
9. Shih, H. C., Chu, S. C., Roddick, J. F., Hung, M. H., & Pan, J. S. (2010). Power reduction of wireless sensor networks using ant colony optimization. In *International Conference on Computational Aspects of Social Networks (CASoN), 2010* (pp. 464–467). IEEE.
10. Handy, M. J., & Haase, M. (2008). Low energy adaptive clustering hierarchy deterministic cluster head selection. In *Advances in Computer Science and Engineering*. Kish Island, Iran.
11. Camilo, T., Carreto, C., Silva, J. S., & Boavida, F. (2006). An energy-efficient ant-based routing algorithm for wireless sensor networks. In M. Dorigo, L. M. Gambardella, M. Birattari, A. Martinoli, R. Poli, & T. Stutzle (Eds.), *ANTS 2006* (Vol. 4150, pp. 49–59)., LNCS Heidelberg: Springer.
12. Zhong, Z., Tian, Z., Li, Z., & Xu, P. (2008). An ant colony optimization competition routing algorithm for WSN. In *4th International Conference on Wireless Communications, Networking and Mobile Computing, 2008* (pp. 1–4). IEEE.
13. Houang, R., Chen, Z. Xu, G. (2010). Energy-aware routing algorithm in WSN using predication-mode. *IEEE 2010*, 978-1-4244-8223-8/10.
14. Amgoth, T., & Jana, P. K. (2014). Energy-aware routing algorithm for wireless sensor networks. *Computers & Electrical Engineering.*
15. Azharuddin, M., & Jana, P. K. (2015). A PSO based fault tolerant routing algorithm for wireless sensor networks. *Information systems design and intelligent applications*, 329–336.
16. Gu, X., Yu, J., Yu, D., Wang, G., & Lv, Y. (2014). ECDC: An energy and coverage-aware distributed clustering protocol for wireless sensor networks. *Computers & Electrical Engineering, 40*(2), 384–398.
17. Kassotakis, I. E., Markaki, M. E., & Vasilakos, A. V. (2000). A hybrid genetic approach for channel reuse in multiple access telecommunication networks. *IEEE Journal on Selected Areas in Communications, 18*(2), 234–243.
18. Attar, A., Tang, H., Vasilakos, A. V., Yu, F. R., & Leung, V. (2012). A survey of security challenges in cognitive radio networks: Solutions and future research directions. *Proceedings of the IEEE, 100*(12), 3172–3186.
19. Li, M., Li, Z., & Vasilakos, A. V. (2013). A survey on topology control in wireless sensor networks: Taxonomy, comparative study, and open issues. *Proceedings of the IEEE, 101*(12), 2538–2557.
20. Duarte, P. B., Fadlullah, Z. M., Vasilakos, A. V., & Kato, N. (2012). On the partially overlapped channel assignment on wireless mesh network backbone: A game theoretic approach. *IEEE Journal on Selected Areas in Communications, 30*(1), 119–127.
21. Jiang, T., Wang, H., & Vasilakos, A. V. (2012). QoE-driven channel allocation schemes for multimedia transmission of priority-based secondary users over cognitive radio networks. *Selected Areas in Communications, IEEE Journal on, 30*(7), 1215–1224.
22. Han, K., Luo, J., Liu, Y., & Vasilakos, A. V. (2013). Algorithm design for data communications in duty-cycled wireless sensor networks: A survey. *Communications Magazine, IEEE, 51*(7), 107–113.
23. Youssef, M., Ibrahim, M., Abdelatif, M., Chen, L., & Vasilakos, A. V. (2014). Routing metrics of cognitive radio networks: A survey. *Communications Surveys & Tutorials, IEEE, 16*(1), 92–109.
24. Xiao, Y., Peng, M., Gibson, J., Xie, G. G., Du, D. Z., & Vasilakos, A. V. (2012). Tight performance bounds of multihop fair access for MAC protocols in wireless sensor networks and underwater sensor networks. *Mobile Computing, IEEE Transactions on, 11*(10), 1538–1554.
25. Fadlullah, Z. M., Taleb, T., Vasilakos, A. V., Guizani, M., & Kato, N. (2010). DTRAB: Combating against attacks on encrypted protocols through traffic-feature analysis. *IEEE/ACM Transactions on Networking (TON), 18*(4), 1234–1247.
26. Liu, X. Y., Zhu, Y., Kong, L., Liu, C., Gu, Y., Vasilakos, A. V., & Wu, M. Y. (2014). CDC: Compressive data collection for wireless sensor networks.
27. Sengupta, S., Das, S., Nasir, M., Vasilakos, A. V., & Pedrycz, W. (2012). An evolutionary multiobjective sleep-scheduling scheme for differentiated coverage in wireless sensor networks. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 42*(6), 1093–1102.
28. Rahimi, M. R., Venkatasubramanian, N., Mehrotra, S., & Vasilakos, A. V. (2012, November). MAPCloud: mobile applications on an elastic and scalable 2-tier cloud architecture. In *Proceedings of the 2012 IEEE/ACM Fifth International Conference on Utility and Cloud Computing* (pp. 83–90). IEEE Computer Society.
29. Vasilakos, A., Saltouros, M. P., Atlassis, A. F., & Pedrycz, W. (2003). Optimizing QoS routing in hierarchical ATM networks using computational intelligence techniques. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 33*(3), 297–312.
30. Liu, L., Song, Y., Zhang, H., Ma, H., & Vasilakos, A. V. (2015). Physarum optimization: A biology-inspired algorithm for the steiner tree problem in networks. *Computers, IEEE Transactions on, 64*(3), 819–832.
31. Meng, T., Wu, F., Yang, Z., Chen, G., & Vasilakos, A. (2015). Spatial reusability-aware routing in multi-hop wireless networks.
32. Chen, M., Gonzalez, S., Vasilakos, A., Cao, H., & Leung, V. C. (2011). Body area networks: A survey. *Mobile Networks and Applications, 16*(2), 171–193.
33. Yan, Z., Zhang, P., & Vasilakos, A. V. (2014). A survey on trust management for Internet of Things. *Journal of Network and Computer Applications, 42*, 120–134.
34. Vasilakos, A. V., & Papadimitriou, G. I. (1995). A new approach to the design of reinforcement schemes for learning automata: Stochastic estimator learning algorithm. *Neurocomputing, 7*(3), 275–297.
35. Zeng, Y., Xiang, K., Li, D., & Vasilakos, A. V. (2013). Directional routing and scheduling for green vehicular delay tolerant networks. *Wireless Networks, 19*(2), 161–173.
36. Jing, Q., Vasilakos, A. V., Wan, J., Lu, J., & Qiu, D. (2014). Security of the internet of things: Perspectives and challenges. *Wireless Networks, 20*(8), 2481–2501.
37. Cheng, H., Xiong, N., Vasilakos, A. V., Yang, L. T., Chen, G., & Zhuang, X. (2012). Nodes organization for channel assignment with topology preservation in multi-radio wireless mesh networks. *Ad Hoc Networks, 10*(5), 760–773.
38. Wei, G., Ling, Y., Guo, B., Xiao, B., & Vasilakos, A. V. (2011). Prediction-based data aggregation in wireless sensor networks: Combining grey model and Kalman Filter. *Computer Communications, 34*(6), 793–802.
39. Yen, Y. S., Chao, H. C., Chang, R. S., & Vasilakos, A. (2011). Flooding-limited and multi-constrained QoS multicast routing based on the genetic algorithm for MANETs. *Mathematical and Computer Modelling, 53*(11), 2238–2250.
40. Liu, Y., Xiong, N., Zhao, Y., Vasilakos, A. V., Gao, J., & Jia, Y. (2010). Multi-layer clustering routing algorithm for wireless vehicular sensor networks. *IET Communications, 4*(7), 810–816.

41. Song, Y., Liu, L., Ma, H., & Vasilakos, A. V. (2014). A biology-based algorithm to minimal exposure problem of wireless sensor networks. *IEEE Transactions on Network and Service Management, 11*(3), 417–430.
42. Li, P., Guo, S., Yu, S., & Vasilakos, A. V. (2014). Reliable multicast with pipelined network coding using opportunistic feeding and routing. *Parallel and Distributed Systems, IEEE Transactions on, 25*(12), 3264–3273.
43. Marwaha, S., Srinivasan, D., Tham, C. K., & Vasilakos, A. (2004, June). Evolutionary fuzzy multi-objective routing for wireless mobile ad hoc networks. In *Evolutionary computation, 2004. CEC2004. Congress on* (vol. 2, pp. 1964–1971). IEEE.
44. Li, P., Guo, S., Yu, S., & Vasilakos, A. V. (2012, March). CodePipe: An opportunistic feeding and routing protocol for reliable multicast with pipelined network coding. In *INFOCOM, 2012 proceedings IEEE* (pp. 100–108). IEEE.
45. Yao, Y., Cao, Q., & Vasilakos, A. V. (2013, October). EDAL: An energy-efficient, delay-aware, and lifetime-balancing data collection protocol for wireless sensor networks. In *Mobile ad-hoc and sensor systems (MASS), 2013 IEEE 10th international conference on* (pp. 182–190). IEEE.
46. Sheng, Z., Yang, S., Yu, Y., Vasilakos, A., Mccann, J., & Leung, K. (2013). A survey on the ietf protocol suite for the internet of things: Standards, challenges, and opportunities. *Wireless Communications, IEEE, 20*(6), 91–98.
47. Xiang, L., Luo, J., & Vasilakos, A. (2011, June). Compressed data aggregation for energy efficient wireless sensor networks. In *Sensor, mesh and ad hoc communications and networks (SECON), 2011 8th annual IEEE communications society conference on* (pp. 46–54). IEEE.
48. Wang, X., Vasilakos, A. V., Chen, M., Liu, Y., & Kwon, T. T. (2012). A survey of green mobile networks: Opportunities and challenges. *Mobile Networks and Applications, 17*(1), 4–20.
49. Chilamkurti, N., Zeadally, S., Vasilakos, A., & Sharma, V. (2009). Cross-layer support for energy efficient routing in wireless sensor networks. *Journal of Sensors*.
50. Busch, C., Kannan, R., & Vasilakos, A. V. (2012). “Approximating congestion+ dilation in networks via” quality of routin; games. *Computers, IEEE Transactions on, 61*(9), 1270–1283.
51. Xu, X., Ansari, R., Khokhar, A., & Vasilakos, A. V. (2015). Hierarchical data aggregation using compressive sensing (HDACS) in WSNs. *ACM Transactions on Sensor Networks (TOSN), 11*(3), 45.
52. Dvir, A., & Vasilakos, A. V. (2011). Backpressure-based routing protocol for DTNs. *ACM SIGCOMM Computer Communication Review, 41*(4), 405–406.
53. Vasilakos, A. V., Zhang, Y., & Spyropoulos, T. (Eds.). (2011). *Delay tolerant networks: Protocols and applications*. Boca Raton: CRC Press.
54. Cobo, L., Quintero, A., & Pierre, S. (2010). Ant-based routing for wireless multimedia sensor networks using multiple QoS. *Computer Networks, 54*, 2991–3010.
55. Camilo, T., Carreto, C., Silva, J. S., Boavida, F. (2006). An energy-efficient ant-based routing algorithm for wireless sensor networks. In *ANTS 2006, LNCS-4150* (pp. 49–59). Heidelberg: Springer.
56. Torres, M. G. (2006). *Energy consumption in wireless sensor networks using GSP*. Medellin, Colombia: Universidad Pontificia Bolivariana.
57. Acharya, A., Seetharam, A., & Bhattacharyya, A. (2009). Balancing energy dissipation in data gathering wireless sensor networks using ant colony optimization. In *LNCS-5408* (pp. 437–443). Heidelberg: Springer.
58. Zhu, X. (2007). Pheromone based energy aware directed diffusion algorithm for wireless sensor network, vol. 4681 (pp. 283–291). Heidelberg: Springer.
59. Farooq, M. & Caro, G. A. (2008). Routing protocols for next-generation networks inspired by collective behaviors of insect societies an overview. *Swarm Intelligence*, 283–291.
60. Eftekhari, P., Shokrzadeh, H., & Haghighat, A. T. (2010). Cluster-base directional rumor routing protocol in wireless sensor network. In *Information and Communication Technologies* (pp. 394–399). Heidelberg, Berlin: Springer.
61. Rivero, J., Cuadra, D., Calle, J., & Isasi, P. (2011). *Using the ACO algorithm for path searches in social networks*. Berlin: Springer.
62. Kolavali, R, & Bhatnagar, S. (2009). Ant colony optimization algorithms for shortest path problems. In *NET-COOP 2008, LNCS 5425* (pp. 37–44) Heidelberg: Springer.
63. Okdem, S, & Karaboga, D., Routing in wireless sensor networks using ant colony optimization. In *Proceedings of the first NASA/ESA conference on adaptive hardware and systems, IEEE.*

Abdolreza Mohajerani received the B.S. degree in communication from Arak University (2013), Arak, Iran, and studding on M.S. in communication-system in Shahid Beheshti University, Tehran, Iran. My main research interests include wireless efficiency and mobile network optimization, stochastic and probabilistic models.

Davood Gharavian was born in Neyshabour, Iran, in 1973. He received the B.S. degree in electronic engineering from Amirkabir University, Tehran, Iran, in 1995 and M.S. in communication engineering from Tarbiat Modares University, Tehran, Iran in 1998 and Ph.D. degrees in electronic engineering from Amirkabir University, Tehran, Iran in 2004. He is currently an Assistant Professor in Electrical Engineering Department of Shahid Beheshti University. His research interests include digital signal processing, speech and image processing, digital signal processor, industrial networks and smart grid. Dr. Gharavian has published more than 21 journal papers and more than 17 conference papers. He is the author of two books in the fields of communication systems and power line carrier.