WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Energy-Efficient Data Gathering and Rendezvous Point Selection with Multiple Mobile Sinks in WSN by using enhanced Clustering and Ant Colony Algorithm

Er. Aman Mishra [#1]

[#1] Assistant Professor, Dept. of CSE, Faculty of Engineering & Technology. KMC Language University

E- Mail: kmishra446@gmail.com

ABSTRACT—

This article introduces an enhanced meta-heuristic optimization algorithm inspired by natural processes. In a wireless sensor network, a mobile sink (MS) is utilized to gather data from individual sensors and transmit it to a base station. To minimize delays in accessing all sensor nodes, the MS can be restricted to specific locations, known as rendezvous points. Many existing techniques rely on static sinks, which can lead to data loss and premature sensor node failure, creating energy-hole problems and diminishing data collection efficiency. To address these challenges, we propose an improved clustering strategy that incorporates multiple mobile sinks and an advanced ant colony optimization (ACO) algorithm for more effective data collection. The performance of the proposed method is evaluated and compared to that of existing algorithms. The approach employs multiple mobile sinks, where the first MS visits a group of cluster heads (CHs), followed by the second MS visiting any remaining unvisited CHs. Consequently, all CHs are visited by a set of MSs. Simulation results indicate that the proposed method significantly enhances network longevity and reduces data loss.

Keywords: Wireless sensor network, Ant colony optimization, Multiple mobile sinks, Clustering, Mobile sink.

1. Introduction

In a transmission scheme, network sensor nodes transmit their data to a base station, while a mobile sink has been proposed as a mechanism for information gathering in wireless sensor networks (WSNs) to manage energy consumption across the sensors geographically. [1]WSN sensor nodes are battery-powered devices that collect data from their environment and relay this information to a sink for analysis.

WSNs play a crucial role in wireless networking, as they gather atmospheric data and send it to a sink node. Many applications of the Internet of Things (IoT) that rely on WSNs are real-time programs that are sensitive to delays, making effective data management essential. Various data collection techniques have been employed in WSNs, including mobile sensors, mobility-based systems, and static sinks. Utilizing these techniques can help reduce data management challenges, power consumption, and data transmission latency.

In wireless sensor networks, multiple sensing devices are interconnected to perform collaborative functions, typically through a multi-hop network. WSNs are utilized in diverse applications, such as environmental monitoring, medical health tracking, industrial monitoring, and many others.

In WSNs, data from sensor nodes are usually transmitted to the sink through multi-hop communication to minimize energy consumption at the nodes. [2] While this data transmission method enhances the overall lifespan of the network, it can also lead to energy issues and the premature failure of sensor nodes. The next objective is to identify the optimal route for the mobile sink, following the selection of the best routing protocols for the network. Recently, artificial intelligence techniques have been applied to tackle complex computational problems, with organically-inspired swarm intelligence algorithms representing a class of these techniques designed to solve optimization challenges. These solutions are determined stochastically by utilizing a set of parameters based on a pheromone model aligned with their variables.

By incorporating a load parameter, rendezvous points (RPs) with higher loads are prioritized during data collection, addressing buffer overflow issues and reducing energy expenditure related to data retention in node buffers. This approach improves the longevity of the WSN. The mobile sink follows a defined data collection path, visiting each RP exactly once before returning to its starting point.

WiFi Sensor Networks (WSNs) can be defined as self-configured and infrastructure networks that monitor physical or environmental conditions, such as temperature, sound, vibration, pressure, motion, or pollutants. The data collected can be collaboratively transmitted through the network to the main site or sink, where it can be analyzed and evaluated.

A wireless sensor network (WSN) consists of numerous small, low-cost sensor nodes equipped with various electronic devices that can sense or control physical parameters in their surroundings. These sensor nodes must work together for specific applications, as a single node is typically insufficient on its own, and they communicate wirelessly with one another.

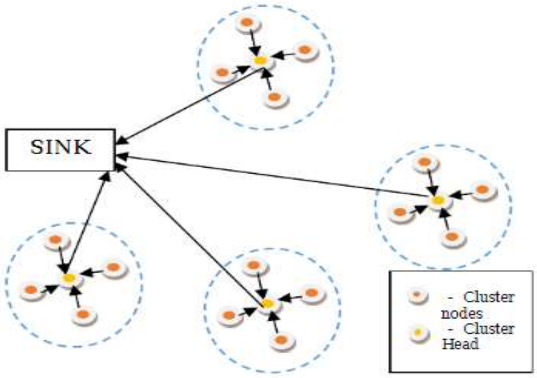

Fig 1.1. Network Topology of WSN

In wireless sensor networks (WSNs), the information gathered from sensor nodes is typically transmitted to the sink via multi-hop connectivity to reduce the energy consumption of the nodes. Although this data transmission method enhances the overall lifespan of the network, it can also lead to energy issues and the premature failure of sensor nodes. Nodes situated near the sink not only forward their own data but also relay information from nearby nodes. [3]Consequently, these proximal nodes tend to deplete their energy more quickly and ultimately fail. This situation complicates the transfer of data from other nodes to the base station, resulting in network distribution challenges, degraded service quality, and reduced system capacity.

Due to various constraints in WSN applications, many existing algorithms aimed at balancing energy consumption among sensors are often difficult to implement. These limitations significantly affect the effectiveness of existing algorithms in practical scenarios. This paper considers a sensor network with multiple mobile sinks deployed to monitor a dynamic region, where the mobile sinks have a locally connected route map. The challenge lies in programming these mobile sinks to gather as much information as possible from sensor devices to extend the network's lifespan. This paper presents the energy efficiency of multiple mobile sinks for sensor networks as a novel constrained optimization problem. We propose an effective solution called the Mobile Sink Movement Algorithm using Artificial Bee Colony optimization, which not only balances the workload among the mobile sinks but also optimizes energy consumption among the sensor nodes.

This study introduces the MWSN data collection strategy, centered around the artificial bee colony algorithm as a reliable and efficient data gathering mechanism. [4]The main contributions of this paper can be summarized as follows: (1) Compilation of mobile sink data, cluster selection optimization, and enhancement of mobile sink paths; (2) Formulation of mobile sink path efficiency as a shortest path problem, utilizing the bee colony technique to optimize solution features and minimize the distance traveled by the mobile sinks, thereby improving data collection efficiency. Honey bees exhibit complex behaviors, including mating, breeding, and foraging, which have inspired various optimization techniques based on their behavior. Given this complexity, we selected bee colony optimization for path optimization in this study. The structure of this paper is organized as follows: Section 1 presents the introduction, Section 2 reviews relevant literature, Section 3 discusses the proposed work, and Sections 4 and 5 present numerical results and conclusions, respectively.

2 Related work

In this article, we review several studies published in recent years regarding various mobile sink (MS) processes, focusing on literature related to mobile sink applications in wireless sensor networks (WSNs).

In previous years, many authors have explored various techniques for data gathering in WSNs, utilizing either static sinks or mobile sinks. The non-uniform energy depletion associated with static sink data collection can lead to reduced efficiency and a shorter network lifespan. Due to the limitations of static sink-based methods, mobility-based approaches have been developed to leverage mobile sinks, achieving better energy balance and reliability. [5] In a direct strategy for mobile sink data collection, the MS visits each node to gather sensed data. However, this method can be time-consuming, resulting in significant delays in the data collection process, which is unsuitable for time-sensitive applications. Some authors have proposed a hybrid system for deploying and repositioning an optimal number of sinks in WSNs.

Researchers have suggested data collection methods for large-scale gathering in delay-sensitive environments, employing mobile sinks that travel in a predefined direction. One author reported a travel planning algorithm aimed at mobile data collection with minimal coverage. Additionally, the authors introduced the Weighted Rendezvous Planning (WRP) method, which selects the most effective rendezvous points (RPs) in a WSN to enhance network lifetime and mitigate energy gaps. They addressed the energy optimization challenge associated with rendezvous nodes and mobile sinks by adopting an ant colony optimization (ACO)-based inter-cluster data aggregation system. In their algorithm, they utilized a traveling salesman problem approach to determine the optimal trajectory among the RPs. In the WRP method, sensor nodes located near the RPs expend significant energy during multi-hop data transmission. The authors also reported an algorithm for selecting groups of RPs in a sensor network while minimizing the travel distance.

The mobile sink is restricted to collecting data from cluster heads (CHs), and the authors employed a k-dimensional cluster-based approach. [6] Due to the forwarding load, nodes close to CHs tend to consume more energy during this process. Consequently, the authors proposed a TCBDGA algorithm aimed at data collection and enhancing network lifetime. This algorithm constructs a tree using a clustering mechanism, with the root of the tree serving as a rendezvous point. As the height of the tree increases, the forwarding load on sensor nodes near the RPs also rises, leading to potential hot-spot problems. To address this issue, sub-RPs were introduced to help balance the tree height [7].

Mottaghi and Zahabi proposed a minimal LEACH clustering algorithm for mobile sinks and rendezvous sensor nodes. This algorithm integrates LEACH, rendezvous points, and mobile sinks to enhance the cluster head selection process while retaining the advantages of LEACH. Compared to traditional LEACH, this algorithm utilizes fewer network resources.

3. Proposed Work

In this, firstly we have a discussion on route formation in which we will have some discussion on the work of MS and Cluster head selection and Secondly, we will use EMMS (Enhanced Multiple mobile sinks) path formation algorithm and MMSBACO (Multiple mobile sinks based Ant colony optimization) to achieve energy-efficient data collection [8].

3.1 Clustering head selection

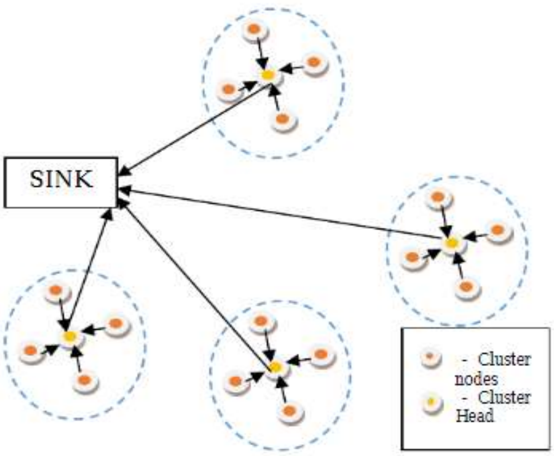

Figure 3.1: Network model for multiple mobile sinks

In the proposed clustering strategy, the modified LEACH algorithm is applied. Sensors are installed in the tracked area and then partitioned into a series of clusters using the steps below. The network's cumulative residual capacity, K_t, is measured as

$$K_t = \sum_{r=1}^{m} K_{rs}(\mathrm{r}) \quad ,$$

where $K_{rs}(r)$ states the node r's residual capacity. The total residual energy of the sensors is then calculated to find a threshold value :

$$E_h = \begin{cases} \frac{Pr_c}{1 - Pr_c(ro_n \bmod 1/Pr_c)} \cdot \frac{K_t}{K_r} & \text{if } h \in S, \\ 0 & \text{otherwise,} \end{cases} \quad \ldots..(2)$$

As Pr_c is the percentage of cluster heads, S is the set of all nodes that are not chosen as a cluster head in the most recent $1/\,Pr_c$ rounds, k_r is the total initial energy of all the nodes in S, and ro_n is the current rounds numbers.

In each round, each sensor creates a random number between 0 and 1. [9] The created number of all sensor is compared with the already defined threshold E_h. As the generated value of the sensor, S_r is less that E_h, S_r is going to be selected as a CH. So then when more than one sensor gives the same value, the node with the maximum residual energy is carried as CH for that specific cluster. Once CH is selected, then they send a message to each sensor node. Finally, to prevent data clashes in the network, the cluster heads transmit time-division multiple access (TDMA) signal messages to their participants with schedule information for data transmission.

3.2 Path Formation

Currently, multiple mobile sink (MMS) methods are garnering significant interest among researchers in wireless sensor networks (WSNs) due to their potential to enhance network lifespan and improve data gathering efficiency. In a WSN environment, we consider an MMS network with KKK cluster heads and NNN mobile sinks. Each mobile sink is assigned to a subset of cluster heads, starting from an initial point. In each round, at least one mobile sink must visit all cluster heads, and each mobile sink should visit at least one cluster head. [10]A primary objective of the proposed solution is to minimize the tour distance for the mobile sinks without compromising data collection.

The challenge of data gathering with mobile sinks is akin to the traveling salesman problem (TSP), which is classified as NP-hard. However, a heuristic algorithm can be employed to find near-optimal solutions.

The proposed routing method consists of the following steps: (i) Each mobile sink is assigned a disjoint subset of cluster heads, and (ii) the order of visits for each mobile sink is determined. An average number of cluster heads is allocated to each mobile sink to optimize energy consumption and achieve a minimal path for every mobile sink.

K_{ch} (MS) = e (CH) /e (MS) ………..(3)

where K_{ch} is the number of CH as- signed to an MS, e (CH) defines the number of CHs, and e (MS) introduced is the number of MSs.

For all MS, the MS member (CH) is issued based on a path matrix, where entries have distance between the CHs and MSs in the network. The distance matrix is introduced as:-

$$d\,(MS, CH) = \begin{bmatrix} l_{11} & l_{12} \cdots & l_{1p} \\ l_{21} & l_{22} \cdots & l_{2p} \\ l_{m1} & l_{m2} \cdots & l_{mp} \end{bmatrix} \quad \ldots\ldots (4)$$

where the row indicates the MS number and the column indicates the CH number. All MS is assigned by CH which is calculated by the minimum value in the concordant column of the above matrix. The below is a more comprehensive explanation.

The member of rth MS where MS_r can be given as a subset of K, That is $K_r \subset K$ ……. (5)

In this r is the index of MS and r = 1, 2, 3, .., m. Based on the conditions below, a subset of CHs (K_r) is generated and given to MS_r . The gap between the CH and MSs d (MS_r, CH_c) in the sensor network is compared. CH_c is assigned to the subset of MS_r, if d (MS_r, CHc) value is minimal in r = 1, 2, 3, ⋯, m. For example, if the gap between MS_2 and the CH_1 is less than other MSs, CH_1 will be assigned to MS_2. So then, all the CH are reported to their corresponding MSs. If a CH has the optimal gap with MMS, then the CH is assigned to any one of the MS.

$\min_{r=1,..m} d(\ MS_r, CH_1)$,…. $\min_{r=1,..m} d(\ MS_r, CH_p)$ --------(6)

For every MSs, MS_r a finite number of disjoint subsets of cluster heads CH_c is formed using (6). So K is partitioned into several disjoint subsets K_r r = 1,.., m, in which $K_r=\{K_{r1},\ldots K_{rl_r}\}$

The *n*th path of the *r*th MS MS_r is given as

$S_{r,n}$ = { Pos_{ini} (*MSr*) , Pos (*Pr*) , Pos_{ini} (*MSr*) } ………(7)

In this Pos_{ini} (*MSr*) indicates the first position of *MSr* and Pos(P_r) represents the CH positions in P_r.

To evaluate the total path gap *pG* traveled by MS_r, we compute the following:

$pG(S_{r,n}) = d(MS_r, P_{r1}) + \sum_{c=1}^{l_r-1} d(K_{rc}, K_{r,c+1}) + d(K_{rl_r}, MS_r)$ ……..(8)

Whereas, *d* (.., ..) indicates the gap between CHs and between a CH and MS. The MS MS_r initiate from the first point, Returns to the starting point after visiting all CHs in P_r in increasing order of indices.

The better sequencing of K_{rc} in K_r is one with less travel length pG($S_{r,n}$). Therefore, to find the sequence of K_{rc} in K_r for every n, now we have given below optimization problem:

$$\min_{S_{r,n}} pG\ (S_{r,n}) \quad \ldots\ldots\ldots\ldots\ldots\ldots(9)$$

So this is a Travelling salesman problem, that is NP-hard. To overcome this problem, we adopt MMSBACO, and which is explained in Section 3.3. and [11] the algorithm below describes the multiple MS path formation.

Algorithm: EMMS Path Formation.

Given: MS coordinate, CH coordinate

Output: Travelling route for MMSs

1: Percentage evaluate average number of CHs assign to MS:

2: K_{ch} (MS) = e (CH) /e (MS)

3: Formation of distance matrix *dMatr*(.., ..) for MSs and CHs by (9)

4: Percentage assignment of CH to the nearby MS

5: using loop c:= 1 to m

6: A= armindMatr(:, c)

7: **end loop**

8: If |A| == 1 it is then

9: Allocate CHc to MS_A

10: **else**

11: Assign CH_c to MS_r, $r \in I$

12: **end if**

13: Call MMSBACO for routing

14: Preparing data gathering

15: Repeat the procedure until the MSs path is established,

3.3 Ant Colony Optimization (ACO)

In the early 1990s, the Ant Colony Optimization (ACO) algorithm [12] emerged as a metaheuristic approach for optimization problems, inspired by the behavior of real ants. Initially developed to address the Traveling Salesman Problem (TSP), which involves determining the shortest route among a set of cities, ACO has since garnered significant attention due to its successful applications in various fields, including network communication, screensavers, cardinality trees, Bayesian networks, serial ordering, and ranking guidelines.

The ACO algorithm generates solutions iteratively, with multiple artificial ants constructing solutions at each step. In the context of the TSP, each ant builds a route by visiting one city at a time until all cities have been visited. As an ant constructs its solution, it selects the next city to visit based on the pheromone concentration associated with each option. This pheromone value plays a crucial role in enhancing the efficiency of the solution. The best solution generated by the ants is informed by the pheromone levels at the end of the iteration and is compared to the optimal solution from the previous iteration, guiding subsequent searches.

ACO often outperforms other algorithms, making it suitable for applying the Mobile Sink Based Ant Colony Optimization (MMSBACO) method to find an optimized path from cluster heads (CHs) while ensuring energy-efficient data gathering. [13]This method was designed to address issues such as hot spots and data loss, ultimately extending the lifespan of wireless sensor networks (WSNs). In this framework, the base station identifies the locations of the CHs and utilizes ACO to determine the paths for the mobile sinks. According to the MMSBACO approach, the first mobile sink travels to a group of CHs, followed by the second mobile sink visiting the next group of unvisited CHs. This process ensures that all CHs are covered by the mobile sinks.

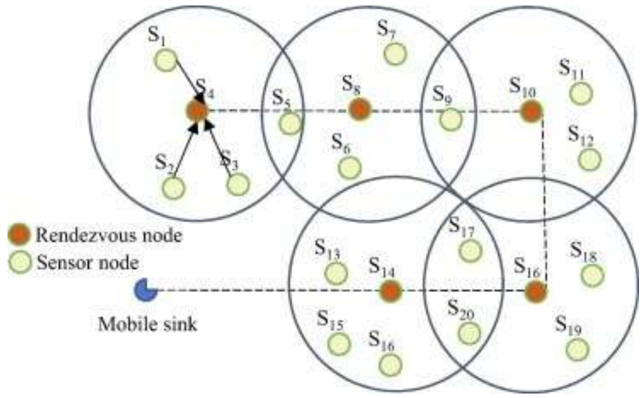

Fig 3.2. WSN Data Collection using ACO

The number of mobile sinks varies from 1 to mmm to evaluate their performance. [14] The primary objective of MMS is to optimize the routing path, contributing to an increase in the network's lifespan. Through this approach, an effective solution is generated, utilizing nnn artificial ants to produce nnn potential solutions.

3.4. Path optimization

In this, for ant colony-based path minimization, every ant finds the new CH appropriately. The given below formula is used for the probability $\mathrm{Pro}(t)^n_{rc}$ of the nth ant moving from the CH r to the CH c:

$$\mathrm{Pro}(t)^n_{rc} = \begin{cases} \dfrac{[\rho_{rc}(t)]^{\beta}[\tau_{rc}]^{\gamma}}{\sum[\rho_{rl}]^{\beta}.[\tau_{rl}]^{\gamma}} & , \ c \in \text{allowed}_n \\ 0 \end{cases}$$

So that ρ_{rc} (t) is the pheromone stored on the route from the rth CH to cth CH., which is expressed from the strength of the pheromone in between the rth CH and cth CH. τ_{rc} can be calculated by the $1/d_{rc,}$ in which d_{rc} is gap between the CH r to CH c. and the allowed_n indicates the CH that unvisited by ant n. Then β and γ are the constant parameters, and this parameter also suggests the ants in decision making.

So to achieve good output, the pheromone values of the ants are updated in every step. Which helps ant performance and gives a better solution.[15] The trail updating method has local and global updation. The local update can be carried out by given below equation :

$\rho_{rc}\,(t+1)$ = (1- η). $\rho_{rc}\,(t) + \Delta\rho_{rc}$

In which η indicates the rate of pheromone evaporation, which can manage the speed of evaporation, t tells the number of steps counter, η∈[0,1] is a value that controls the degradation of ρ_{rc} and it is the pheromone count in the present step, that is distributed on the edges. and $\Delta\rho_{rc}$ can be calculated as:

$\Delta\rho_{rc} = \sum_{n=1}^{M} \Delta\rho_{rc}^{n}$

In this each ant n left behind the rth CH and reached the cth CH leaves a certain amount of pheromone behind is evaluated by

$\Delta\rho_{rc}^{n} = \frac{V}{L_{rc}}$,

In the above equation V is constant and L_{rc} is the distance in which ant n moves from the CH_r to the CH_c.

This upgrade mechanism allows it to find a shorter path and improves the chances of finding the best optimal path. This method is replicated before the predetermined amount of iterations has been completed or a suitable answer has been discovered. [16]The final output can be thought of as the best way for an MS to travel.

4. Conclusion

To enhance data gathering performance and extend the lifespan of wireless sensor networks (WSNs), we propose a novel solution based on multiple mobile sinks (MMS). This approach employs a modified LEACH-based clustering technique to organize sensor nodes and select cluster heads. In this context, the mobile sink operates like a robotic agent, collecting data from the cluster heads throughout the network.

The ACO-based mobile sink solution makes routing more effective and adaptable to changes in the WSN topology. By utilizing this method, the time required to collect data from clusters is reduced, leading to increased network longevity and minimizing data loss. Simulation results indicate that the new routing scheme significantly decreases overall travel distance compared to existing algorithms. Furthermore, unlike traditional systems that rely solely on a static sink, this approach has the potential to greatly enhance the network's lifespan. Future work could involve integrating the mobile sink with other bio-inspired algorithms to assess their effectiveness, taking into account the mobility of sensor nodes

Table 4.1: Comparison Table

No. of CH	Alg.	M=1	M=2	M=3
10	LEACH	695.3201	696.7107	712.5994
	GA	640.1803	645.7826	652.6086
	PSO	567.2219	565.7812	598.1218
	Prop.	540.4212	540.4212	544.1588
20	LEACH	976.1456	970.8788	970.8788
	GA	924.1587	924.1587	912.4044
	PSO	892.3862	891.2813	891.1049
	Prop.	840.2244	846.1592	853.8613
30	LEACH	1133.7891	1137.1888	1119.8383
	GA	1070.1621	1088.4103	1096.5366
	PSO	1010.3861	1013.9038	1017.4618
	Prop.	0988.7075	0996.1931	0997.9895

5. References

G. Eason, B. Noble, and I.N. Sneddon, “On certain integrals of Lipschitz-Hankel type involving products of Bessel functions,” Phil. Trans. Roy. Soc. London, vol. A247, pp. 529-551, April 1955. (*references*)

J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1892, pp.68-73.

I.S. Jacobs and C.P. Bean, “Fine particles, thin films and exchange anisotropy,” in Magnetism, vol. III, G.T. Rado and H. Suhl, Eds. New York: Academic, 1963, pp. 271-350.

K. Elissa, “Title of paper if known,” unpublished.

R. Nicole, “Title of paper with only first word capitalized,” J. Name Stand. Abbrev., in press.

Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740-741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

M. Young, The Technical Writer’s Handbook. Mill Valley, CA: University Science, 1989.

T. Rault, A. Bouabdallah, Y. Challal, Energy efficiency in wireless sensor networks: A top-down survey, Computer Networks 67 (2014) 104 – 122.

M. Krishnan, V. Rajagopal, S. Rathinasamy, Performance evaluation of sensor deployment using optimization techniques and scheduling approach for k-coverage in wsns, Wireless Networks 24 (3) (2018) 683–693.

M. Dong, X. Liu, Z. Qian, A. Liu, T. Wang, Qoe-ensured price competition model for emerging mobile networks, IEEE Wireless Communications 22 (4) (2015) 50–57.

Y. Yun, Y. Xia, Maximizing the lifetime of wireless sensor networks with mobile sink in delay-tolerant applications, IEEE Transactions on Mobile Computing 9 (9) (2010) 1308–1318.

H. U. Yildiz, K. Bicakci, B. Tavli, H. Gultekin, D. Incebacak, Maximizing wireless sensor network lifetime by communication/computation energy optimization of non-repudiation security service: Node level versus network level strategies, Ad Hoc Networks 37 (2016) 301 – 323.

T. Bhatia, S. Kansal, S. Goel, A. Verma, A genetic algorithm based distance-aware routing protocol for wireless sensor networks, Computers & Electrical Engineering 56 (2016) 441 – 455.

W.-H. Liao, Y. Kao, R.-T. Wu, Ant colony optimization based sensor de- ployment protocol for wireless sensor networks, Expert Systems with Applications 38 (6) (2011) 6599 – 6605.

W. B. Heinzelman, A. P. Chandrakasan, H. Balakrishnan, An application- specific protocol architecture for wireless microsensor networks, IEEE Transactions on Wireless Communications 1 (4) (2002) 660–670.

A. M. Adrian, A. Utamima, K.-J. Wang, A comparative study of ga, pso and aco for solving construction site layout optimization, KSCE Journal of Civil Engineering 19 (3) (2015) 520–527.