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On Lifetime Enhancement of Super Nodes based Wireless Sensor Networks by using Sine Cosine Algorithm

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Wireless Sensor Networks (WSNs) are consists of many tiny sensing devices called nodes to sense, compute and transmit the data. These nodes are made of transducer, memory, battery, micro-controller and an antenna for the communication of data from node to sinks. Nodes used in the networks are having energy constraints as they are usually battery powered and hence it is not always feasible to change the battery due to odd terrain of deployment. For the managements of these limited energy resources of WSNs various algorithms have been proposed and implemented. In this paper we have implemented the Sine Cosine Optimization algorithm in routing and clustering of WSNs for the optimizing lifetime of the Wireless Sensor Networks. Higher energy nodes are deployed to work as the cluster head to enhance the lifetime of WSNs and effect of using higher energy nodes are also studied for two different position of base station (BS). Results of this algorithm are compared with the Genetic Algorithm and Particle Swarm Optimization Algorithm.

Keywords: wireless sensor networks, clustering, routing, particle swarm optimization, genetic algorithm, sine cosine algorithm

1. INTRODUCTION

WSNs are consists of very huge number of sensor nodes and each node is capable of sensing the physical quantities, transducers to convert them into binary data, micro controller for data aggregation *etc.*, memory for storage of data, battery for power supply to the sensing nodes and antenna for communicating the data to the next node or sink. These networks utilized for various applications from sensing, tracking, monitoring, measurements and medical [1-3]. Usually these sensor nodes are attached with the low powered battery, so recharging or replacing is required to keep alive the sensor nodes. But as these sensors are deployed in the odd terrain so it is very hard to replace them or recharge them. Numerous algorithms are being implemented to manage the battery powered resources through the energy aware routing and energy efficient clustering for en-

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hancing the overall lifetime of WSNs [4-6]. Apart from battery sources managements, various energy harvesting technologies are being implemented to make these sensor nodes as energy harvesting nodes so that these nodes can generate the energy for their use without any external power source [7-10]. Some heterogeneous networks are also implemented for increasing the lifetime of WSNs. But still this technology is in its early phase of evolution. Recently simultaneous wireless information and power transfer (SWIPT) technologies are in the developments to overcome the limitation of power supply in the Wireless Sensor Networks [11-13]. Also various researches are also have been carried out for increasing the coverage and data efficiency of the wireless sensor networks [14-16].

Various optimization methods have been implemented to enhance the lifetime of the WSNs [17-19]. At first Low Energy Adaptive Clustering Hierarchy (LEACH) is proposed by Heinzelman in [20]. In this algorithm cluster head (CH) is selected on the basis of their energy and accessibility and also sensor nodes accomplish data fusion for the compression of data. In [21], a survey has been conducted for various aspects of using particle swarm optimization in wireless sensor networks and in its various applications. In [22], a hierarchical routing based approach taken for the lifetime enhancement in wireless sensor networks. A novel clustering scheme proposed in [23], according to which a member sensor node may join a distant CH in order to achieve the better energy efficiency. In [24], A Novel Clustering Algorithm for Energy Efficiency (ANCAEE) for WSN has been proposed to minimize energy consumption by its uniform distribution among all nodes. Base station controlled dynamic clustering protocol (BCDCP) has been proposed in [25], to achieve uniform energy consumption at every node for improving network lifetime and to increase average energy saving. It is also compared with existing protocols like Power Efficient Gathering in Sensor Information System (PEGASIS) and it has been found that it is working better than all of them. In [26], an energy efficient clustering protocol based on K-means midpoint algorithm has been proposed to improve cluster structure, optimize the selection of CHs and reduce energy consumption for data transmission.

The concept of higher energy nodes used in the [27], in which these higher energy nodes are used to work as the CHs. In [27], the particle swarm optimization algorithm [28] is used to achieve the energy efficient clustering and routing. Optimized Energy Efficient Resolution Protocol (OEERP) is proposed in [29]. In this scheme the cluster heads change in each next time slot and this approach improves the lifetime of WSNs. An improvement over OEERP is proposed in [30] as E-OEERP (Efficient-OEERP). In this scheme preferable residual nodes are become CHs in the next time slot. It is shown that less numbers of residual nodes are formed in this scheme. Data Routing for In-Network Aggregation (DRINA) is a scheme proposed in [31]. In this protocol the higher data aggregation is achieved and also it tries to increase the overlapping path during the communication of data.

Clusterheads have to take part in the cluster formation and also have to work as the relay nodes to forward the data towards the BS. To handle this heavy workload, some dedicated nodes with higher energy deployed in the WSNs to work as the CHs and to handle the clustering and routing process efficiently. In this paper we have applied Sine Cosine Optimization Algorithm [32] for energy aware routing and for energy efficient clustering of WSNs. This algorithm was previously never used in this heterogeneous type of networks *i.e.* when higher energy CHs are used. The upcoming results when compared with the results of Least Distance Clustering (LDC) [27], PSO [28] and Genetic Algorithm (GA) [33]. SCA outperforms the other three previously used algorithms. The results are also been analyzed for the variable position of BS. In this paper two position of BS are taken for comparison purpose. The total number of hops that are formed in the networks are also compared for the all three optimization algorithms mentioned above. It has been found that with the use of SCA, total number of hops reduces which indicates that it has also optimized the number of intermediate nodes required in the efficient way. So, in this work we report a better energy efficient clustering and energy aware routing along with enhanced lifetime of WSNs for equal population of sensing nodes and supernodes. This is an important novel aspect of the work and it provides a new dimension towards energy efficient network design research, with a higher lifetime of WSNs.

2. INTRODUCTION TO ENERGY MODEL USED

In this paper the energy expenditure model is used as in [20]. In this energy model free space fading channel model and multipath fading channel model both are used. In this model a threshold distance is described to decide the model to be used. When the transmission distance is less than a threshold distance then the free space fading channel model is considered and if the transmission distance is greater than this threshold distance then multipath fading channel model is considered [20].

$$\begin{aligned} E_{TX}(l, d) &= E_{Tx\text{-}elec}(l) + E_{Tx\text{-}amp}(l, d) \\ &= lE_{elec} + l\xi_{fs}d^2 \qquad \text{for } d < d_0 \\ &= lE_{elec} + l\xi_{mp}d^4 \qquad \text{for } d \geq d_0 \end{aligned}$$

and

$$E_{RX}(l) = E_{Rx\text{-}elec}(l) = lE_{elec}. \tag{1}$$

here $E_{Tx\text{-}elec}(l)$ denotes the requirement of energy by the transmitter and $E_{Rx\text{-}elec}(l)$ denotes the requirement of energy by the receiver for transmitting of l bits of message. E_{elec} represents the requirement of energy of electronic circuit for transmission of per bit of message. $E_{Tx\text{-}elec}(l)$ represents the amplification energy for the per bit of message. $E_{Tx}(l, d)$ is the energy requirement for the transmission of l bits of message to the distance d and d_0 denotes the threshold distance. ξ_{mp} and ξ_{fs} represent the requirement of energy by the amplifier in the multipath and free space scenarios respectively. Basic energy model has been demonstrated in the Fig. 1 below.

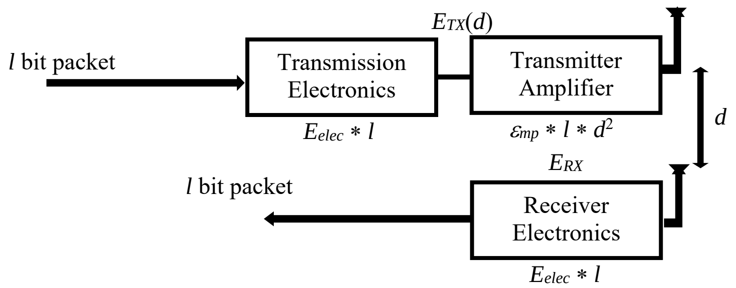


Fig. 1. Block diagram of first order energy model.

3. BRIEF INTRODUCTION OF ALGORITHMS USED

In this paper four algorithms have been used for the clustering and routing in wireless sensor networks. The brief introduction of algorithms is given below:

3.1 Least Distance Clustering

The least distance clustering is employed in wireless sensor networks during the cluster formation phase and routing phase. In the cluster formation phase, distance from sink-node to each supernode is calculated and then sorted on the basis of their lowest distance from sink-node. For each sensor node present in the network, supernodes are designated which are within the communication range of sensor nodes. The super nodes from this designated group and having the least distance from sink-node selected as cluster-head for sensor node. In the routing phase, this process is repeated for the selection of next-hop for each supernode to ensure the longer life of sensor network [27].

3.2 Genetic Algorithm

A genetic algorithm is one of basic algorithm that searches the solution space to find the optimal solution to a given problem [33]. The main feature of genetic algorithm is that how the searching is done. First of all, the algorithm creates the "population" of possible solutions also called initial population. Each individual is represented by array or group of genes, which is called chromosome. The solution given by each chromosome is evaluated by a fitness function. In the crossover process, parents swap their genes to produce new children. If the fitness of children is better than the least two fitness of chromosome then they included in the population and the chromosome having the least fitness discarded from the population. The mutation process is executed with the help of the fitness value of individual by discarding the individual with the lowest fitness. This process repeated over multiple generation to get the optimized solution for the problem.

3.3 Particle Swarm Optimization

PSO is a heuristic optimization technique [28]. In PSO, each particle has its own memory and shares the information with its neighbours to maintain collective intelligence. While implementing PSO, numerous considerations must be taken for convergence which includes limiting maximum velocity, the constriction factor, selection of acceleration constant and inertia weight. At first, a large number of initial population of particles generated as well as distributed randomly in the search space. If N_p is the total number of particles then each particle in the search space gives the complete solution to the multi-dimensional optimization problem. In this algorithm, the optimization is done using the two equations namely velocity and update equations. Which are given below as:

$$V_{i,d}(t) = w \times V_{i,d}(t-1) + c_1 \times r_1 \times (Xpbest_{i,d} - X_{i,d}(t-1) + c_2 \times r_2 \times (Xpbest_d - X_{i,d}(t-1), \quad (2)$$

$$X_{i,d}(t) = X_{i,d}(t-1) + V_{i,d}(t). \quad (3)$$

Where $X_{i,d}(1 \le d \le D)$ is the position for the i^{th} particle and in the d^{th} dimension of provided search space. Best of a particle is represented by P_{best} and each particle follow its own best position $X_{i,d}$ with the help of its velocity $V_{i,d}$ to attain the global G_{best}. Here each particle has its own fitness function to judge the quality of the solution provided by it. Here the velocity and position in the d^{th} dimension is updated by the using the above equations respectively, w denotes the inertial weight, c_1 and c_2 represent acceleration factors and are non-negative constants. Here r_1 and r_2 are two different uniformly distributed random numbers between 0 and 1.

3.4 Sine Cosine Algorithm

The SCA (Sine Cosine Algorithm) generates numerous primary solutions and help to move far or near to the best solution of problem by using a mathematical model which is depending on trigonometric functions. The two equations are proposed for updating the position for exploration stage and exploitation purpose are given below [32]:

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t| \tag{4}$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_{ii}^t| \tag{5}$$

where X_i^t represents the position of the present solution of the problem in the i^{th} dimension and t^{th} iteration, here $r_2/r_2/r_3$ represents random numbers and P_i represents the location of the terminus point in the i^{th} dimension in search space and absolute value is indicated by ||. Two equations are combined here as given below [32]:

$$X_i^{t+1} = \begin{cases} X_i^t + r_1 \times \sin(r_2) \times |r_3 P_i^t - X_i^t|, \ r_4 < 0.5 & (6) \\ X_i^t + r_1 \times \cos(r_2) \times |r_3 P_i^t - X_{ii}^t|, \ r_4 \geq 0.5 & (7) \end{cases}.$$

In the above equation r_4 denotes a random number with the range of [0, 1]. As shown above r_1, r_2, r_3 and r_4 are four main parameters. r_1 directs the successive position's space that might be located either within the search space or outside it. Here r_2 defines the movement into or outward the target and random number r_3 gives a random weight for terminus for stochastically emphasizing ($r_3 > 1$) or de-emphasizing ($r_3 < 1$) the outcomes of terminus. Random number r_4 switches amid the sine and cosine parts in Eqs. (6) and (7) equally. It is note-worthy that above mentioned equations may be involved to solve the various high dimensions and complex problems. The recurring way of navigating of these functions allow a result to be re-positioned near supplementary solution. The random position either within or outside of loop is achieved by outlining r_2 in $[0, 2\pi]$ in above Eqs. (6) and (7), which guarantees exploration and exploitation process both. To keep balance in both processes, the range of functions in Eqs. (4)-(7) is changed with the use of the next equation given below [32]:

$$r_1 = a - t \times \frac{a}{T}. \tag{8}$$

In the above Eq. (8), variable t denotes the present iteration. 'a' is a constant while T denotes the highest number of iterations. It also having a fixed value. Above equation reduces the range of Eqs. (6) and (7) with the iterations. It starts for the process with a group of random solutions to the problems. It concludes the optimization procedure with the number of iteration advances further to a predefined number. Some other different termination situation can also be engaged.

4. SCA BASED APPROACH TO THE 'LIFETIME ENHANCEMENT' PROBLEM IN WSNs

SCA has been applied for energy aware routing as well as in energy efficient clustering of the wireless sensor networks. SCA generates and does improvement in a group of random solutions. It fundamentally gained by using extraordinary exploration as well as local optima prevention and equated with individual based algorithms. Numerous segments of the search space of problem are covered by algorithm in the case when sine and cosine function equations omit a value greater than 1 or less than −1. When the trigonometric functions return values between −1 and 1, then it explores the promising region of any given search space.

In this paper energy efficient clustering is accomplished for eight different CHs population. For generalization, it is assumed that total number of supernodes that are present in the network are M and population of sensor nodes is N. Then in the case of clustering when SCA is used for the cluster formation then the dimension of the problem is same as the number of sensor nodes *i.e.* N and when routing takes place then dimension of the problem is equal to the population of the super nodes present in the WSNs *i.e.* M. Total number of agents used for solving the clustering and routing problem is taken at 50. The average lifetime has been calculated for the 20 runs of algorithms with 200 iterations each.

For energy aware routing fitness function is given by:

$$F_1 = P \times (MaxDist - MinDist) + Q \times MaxHop. \tag{9}$$

Here *MaxHop* is denotes the maximum number of hops and *MaxDist* denotes the maximum communication distance between the supernode and next-hop. *MinDist* denotes minimum communication distance between the nodes and supernodes. Here P and Q represent constants such that addition of P and Q is unity. Our motive is to minimize the value of *MaxDist* and *MaxHop* both in the network. But as there is a trade-off between them as if we decrease the *MaxDist* then the value of number of *Maxhop* increases means more number of hopes required to send the data to the sink node and vice versa.

For energy efficient clustering fitness function is:

$$F_2 = L / \sum_{i=1}^{N} rms\_avg\_Dist. \tag{10}$$

Where *rms_avg_Dist* represents the average of root mean square distance between each sensor node to their respective CH. N is the total number of sensor nodes present in the network while L represents the lifetime. Here objective is to maximization of the lifetime of the supernodes and also we want to minimize the average distance between the nodes and supernodes for minimizing the energy consumption. So here it is required to maximize the fitness function F_2.

The total energy consumption of the super nodes may be distributed into total four parts that can be given as:

$$E_{total}(CH) = E_R + E_D + E_T + E_F. \tag{11}$$

Where E_R denotes the consumption of energy in reception of the packets by CH. Here E_D and E_T denote the energy consumption for the data aggregation and transmission of data packets. E_F represents the energy requirements to forward the incoming packets coming from the previous CHs *i.e.* it denotes the energy expenditure of the CH while it works as the relay nodes.

5. SIMULATIONS AND RESULTS

Experiments have been carried out with the help of C programming language and MATLAB R2013a software. Total population of sensor nodes are varied from 200 to 500 for different cases. While the population of super nodes are varied from 20 and 90 for different cases. Each sensor nodes are given the energy of 0.5 J and each super node having the energy of 10 J. The values of various parameters that are used in the simulation study is given below in Table 1 [20, 27].

The communication range of both the sensor node and super nodes are fixed upto 150 m. The threshold distance is taken at 87 m, which decides that free space or multipath channel model will be utilized. If the distance of communication is less than the threshold distance then free space channel model is used and if the distance of communication is more than this threshold distance then multipath fading channel is used. Here each of the node and super nodes will generate the packets of size 1024 bits and that will be send forward it to the next CH or sink node depending on the distance between them. When the BS is positioned at the center (250, 250) of network then network is donated as WSN_1 and when the BS is positioned at the corner (500, 500) of the network then it is denoted by WSN_2.

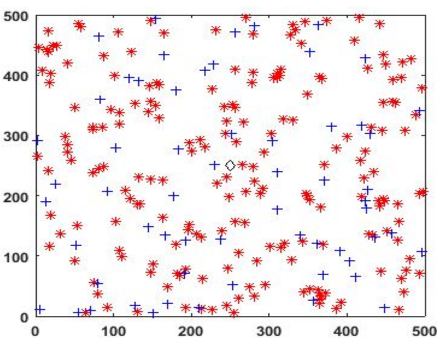


Fig. 2. Deployment of sensors in the wireless sensor network with base-station at the center.

In the above figure, the wireless sensor network with the Base-Station at the center has been demonstrated. In the above figure '*' represents the sensor node deployment and '+' represents the super nodes present in the networks. Base-Station is demonstrated by the diamond sign located at the center.

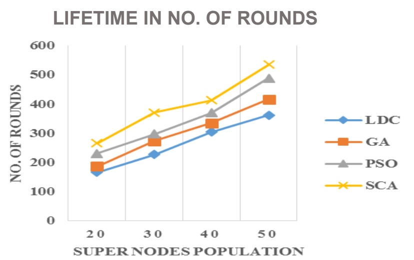
Table 1. Network parameters.

Parameters	Values
Area of wireless sensor network	500×500 metre^2
Population of sensor nodes	200-500
Supernodes	20-90
Initial energy provided to sensor nodes	0.5 Joule
Maximum number of iterations	200
Communication range of sensor nodes and super nodes	150 metres
Energy required by electronic circuit (E_elec)	50nJ/bit
Amplification energy of Free space (ξ_{fs})	10 pJ/bit/metre^2
Amplification energy of multipath (ξ_{mp})	0.0013 pJ/bit/metre^4
Threshold distance (d_0)	87.0 metres
Data Aggregation Energy (E_{DA})	5nJ/bit
Packet Size	1024 bits
Initial energy of each supernode	10 J

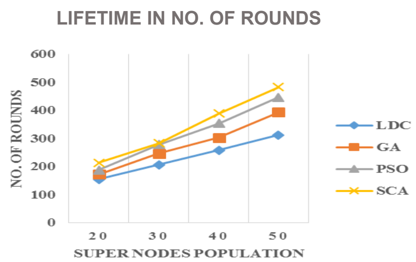
Table 2. Lifetime of wireless sensor networks for supernodes population from 20 to 50 for WSN_1 and WSN_2.

No of super nodes	WSN_1				WSN_2			
	20	30	40	50	20	30	40	50
Lifetime with LDC	165	226	303	361	154	205	257	311
Lifetime with GA	185	272	334	415	172	246	302	393
Lifetime with PSO	230	296	369	488	187	277	352	445
Lifetime with SCA	265	371	412	534	212	282	388	482

Fig. 3 (a) below represents the lifetime of sensor networks when total number of super nodes population is varied from 20 to 50 and total number of sensor nodes are deployed are fixed at 300. In this case the BS is positioned at the center of the sensor network area. The outcomes are compared in terms of lifetime of sensor networks while employing the four different algorithms namely LDC, GA, PSO and SCA. It has been seen that SCA performs better than all the other three algorithms mentioned above.



(a)

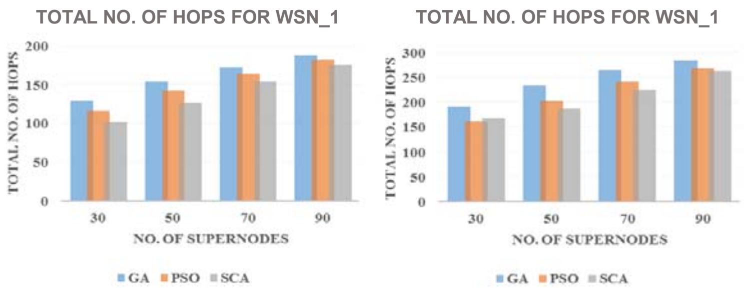


(b)

Fig. 3. Supernodes variation from 20-50 for (a) WSN_1 and (b) WSN_2.

Fig 3 (b) above denotes the lifetime of WSN_2 while variation in supernodes population is done from 20 to 50 and keeping total number of sensor nodes population is fixed at 300. All the corresponding values for Figs. 3 (a) and (b) are shown above in Table 2. In this case, the BS is positioned at the corner of the network. The outcomes from this case are compared in terms of lifetime of network while employing the four different algorithms same as the above case in Fig 3 (a). It has been found that SCA again out-performs all the other three algorithms mentioned above.

In the Figs. 4 (a) and (b) above, the total number of Hops are compared by using three different algorithms namely GA, PSO and SCA. It is observed that number of Hops is increased while increment in the supernodes in the wireless sensor networks. It has been also observed that less number of Hops formed in both types of sensor networks *i.e.* WSN_1 and WSN_2 while SCA is used.



(a) (b)

Fig. 4. Total number of hops formed for (a) WSN_1 and (b) WSN_2.

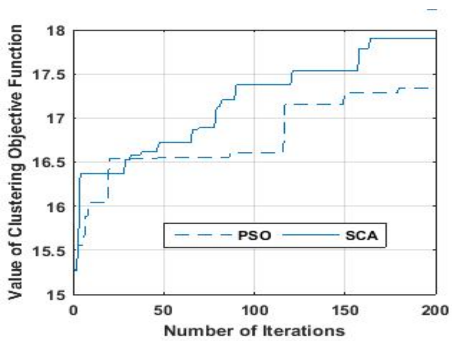


Fig. 5. Maximization of the objective function of clustering by using PSO and SCA.

In the Fig. 5, the optimization of the objective function of clustering has been demonstrated for the 200 iterations. In the figure below, the total population of the sensor nodes are taken at the 200 while the total population of the supernode is 50. In Fig. 5, the objective function of clustering has been maximised using the Sine Cosine Optimization Algorithm and Particle Swarm Optimization algorithm. It can be seen from the figure below that the while using the Sine Cosine Optimization Algorithm, clustering objective function achieves the more optimum value as the iteration goes ahead as compared to Particle Swarm Optimization algorithm.

It is very clear from all the above analysis that Sine Cosine Optimization Algorithm is performing better in the different changing scenarios and varying conditions. It is also evading the local optima and also escaping the premature convergence for the better results.

6. CONCLUSIONS

Sine Cosine Algorithms have been implemented to enhance the lifetime of the sensor networks. Coming results with this algorithm are compared with the other optimization algorithms. The some higher energy nodes are deployed for increasing the lifetime of the WSNs. The population of these higher energy nodes vary to demonstrate the effect more clearly. All the results are evaluated for the two different positions of the Base-Station. It has been found that Sine Cosine Optimization Algorithm is showing better results than the all other algorithms used. Further some hybrid algorithms can be used for the enhancing the lifetime of the sensor networks.

REFERENCES

1. N. Cao, S. Choi, E. Masazade, and P. K. Varshney, "Sensor selection for target tracking in wireless sensor networks with uncertainty," *IEEE Transactions on Signal Processing*, Vol. 64, 2016, pp. 5191-5204.
2. Y. Fu, Q. Ling, and Z. Tian, "Distributed sensor allocation for multi-target tracking in wireless sensor networks," *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 48, 2012, pp. 3538-3553.
3. K. Li, W. Ni, X. Wang, R. P. Liu, S. S. Kanhere, and S. Jha, "Energy-efficient cooperative relaying for unmanned aerial vehicles," *IEEE Transactions on Mobile Computing*, Vol. 15, 2016, pp. 1377-1386.
4. S. Shah and B. Beferull-Lozano, "Joint sensor selection and multihop routing for distributed estimation in ad-hoc wireless sensor networks," *IEEE Transactions on Signal Processing*, Vol. 61, 2013, pp. 6355-6370.
5. J. W. Jung and M. A. Weitnauer, "On using cooperative routing for lifetime optimization of multi-hop wireless sensor networks: analysis and guidelines," *IEEE Transactions on Communications*, Vol. 61, 2013, pp. 3413-3423.
6. S. Kumar, "Compartmental modeling of opportunistic signals for energy efficient optimal clustering in WSN," *IEEE Communications Letter*, Vol. 22, 2018, pp. 173-176.
7. N. Michelusi, L. Badia, R. Carli, L. Corradini, and M. Zorzi, "Energy management policies for harvesting-based wireless sensor devices with battery degradation," *IEEE Transactions on Communications*, Vol. 61, 2013, pp. 4934-4947.
8. J. C. Kwan and A. O. Fapojuwo, "Radio frequency energy harvesting and data rate optimization in wireless information and power transfer sensor networks," *IEEE Sensors Journal*, Vol. 17, 2017, pp. 4862-4874.
9. C. Wang, S. Guo, and Y. Yang, "An optimization framework for mobile data collection in energy-harvesting wireless sensor networks," *IEEE Transactions on Mobile Computing*, Vol. 15, 2016, pp. 2969-2986.
10. P. H. Zhou, T. Jiang, C. Gong, and Y. Zhou, "Optimal estimation in wireless sensor networks with energy harvesting," *IEEE Transactions on Vehicular Technology*, Vol. 65, 2016, pp. 9386-9396.
11. Y. Lin, J. Zhang, H. S-H. Chung, W. H. Ip, Y. Li, and Y.-H. Shi, "An ant colony optimization approach for maximizing the lifetime of heterogeneous wireless sensor

networks," *IEEE Transactions on Systems, Man and Cybernetics – Part C: Applications and Reviews*, Vol. 42, 2012, pp. 408-420.
12. G. Pan, H. Lei, Y. Yuan, and Z. Ding, "Performance analysis and optimization for SWIPT wireless sensor networks," *IEEE Transactions on Communications*, Vol. 65, 2017, pp. 2291-2302.
13. S. Guo, F. Wang, Y. Yang, and B. Xiao, "Energy-efficient cooperative transmission for simultaneous wireless information and power transfer in clustered wireless sensor networks," *IEEE Transactions on Communications*, Vol. 63, 2015, pp. 4405-4417.
14. T. Shu and M. Krunz, "Coverage-time optimization for clustered wireless sensor networks: A power-balancing approach," *IEEE Transactions on Networking*, Vol. 18, 2010, pp. 202-215.
15. A. Adulyasas, Z. Sun, and N. Wang, "Connected coverage optimization for sensor scheduling in wireless sensor networks," *IEEE Sensor Journal*, Vol. 15, 2015, pp. 3877-3892.
16. T. F. da Silva and D. G. Costa, "Centralized algorithms for redundant coverage maximization in wireless visual sensor networks," *IEEE Latin America Transactions*, Vol. 14, 2016, pp. 3378-3384.
17. E. Fitzgerald, M. Pióro, and A. Tomaszewski, "Energy-optimal data aggregation and dissemination for the internet of things," *IEEE Internet of Things Journal*, Vol. 5, 2018, pp. 955-969.
18. J. Wang, J. Cao, B. Li, S. Lee, and R. S. Sherratt, "Bio-inspired ant colony optimization based clustering algorithm with mobile sinks for applications in consumer home automation networks," *IEEE Transactions on Consumer Electronics*, Vol. 61, 2015, pp. 438-444.
19. X. Liu, "An optimal-distance-based transmission strategy for lifetime maximization of wireless sensor networks," *IEEE Sensors Journal*, Vol. 15, 2015, pp. 3484-3491.
20. W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, "An applications specific protocol architecture for wireless microsensor networks," *IEEE Transactions on Wireless Communication*, Vol. 1, 2002, pp. 660-670.
21. R. V. Kulkarni and G. K. Venayagamoorthy, "Particle swarm optimization in wireless-sensor networks: A brief survey," *IEEE Transactions on Systems, Man, and Cybernetics, Part C, Applications and Reviews*, Vol. 41, 2011, pp. 262-267.
22. H. Aoudia, Y. Touati, A. Cherif, and P. Greussay, "Hierarchical routing approach-based energy optimization in wireless sensor networks," in *Proceedings of the 10th ACM International Symposium on Mobility Management and Wireless Access*, 2012, pp. 131-134.
23. D. Xie, Q. Zhou, X. You, B. Li, and X. Yuan, "A novel energy-efficient cluster formation strategy: From the perspective of cluster members," *IEEE Communications Letters*, Vol. 17, 2013, pp. 2044-2047.
24. A. P. Abidoye, N. A. Azeez, A. O. Adesina, and K. K. Agbele, "ANCAEE: A novel clustering algorithm for energy efficiency in wireless sensor networks," *Wireless Sensor Networks*, Vol. 3, 2011, pp. 307-312.
25. S. Chatterjee and M. Singh, "A centralized energy-efficient routing protocol for wireless sensor networks," *International Journal of Advanced Networking and Applications*, Vol. 3, 2012, pp. 12-18.

26. A. Ray and D. De, "Energy efficient clustering protocol based on K-means (EECPK-means)-midpoint algorithm for enhanced network lifetime in wireless sensor network," *IET Wireless Sensor Systems*, Vol. 6, 2016, pp. 181-191.
27. P. Kuila and P. K. Jana, "Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach," *Engineering Applications of Artificial Intelligence*, Vol. 33, 2014, pp. 127-140.
28. J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proceedings of IEEE International Conference on Neural Networks*, 1995, pp. 1942-1948.
29. K. K. Chand, P. V. Bharati, and B. S. Ramanjaneyulu, "Optimized energy efficient routing protocol for life-time improvement in wireless sensor networks," in *Proceedings of IEEE International Conference on Advances in Engineering*, *Science and Management*, 2012, pp. 345-349.
30. J. RejinaParvin and C. Vasanthanayaki, "Particle swarm optimization-based clustering by preventing residual nodes in wireless sensor networks," *IEEE Sensor Journal*, Vol. 15, 2015, pp. 4264-4274.
31. L. A. Villas, A. Boukerche, H. S. Ramos, H. A. B. F. Oliveira, R. B. Araujo, and F. A. A. Loureiro, "DRINA: A lightweight and reliable routing approach for in-network aggregation in wireless sensor networks," *IEEE Transactions on Computer*, Vol. 62, 2013, pp. 676-689.
32. S. Mirjalili, "SCA: A sine cosine algorithm for solving optimization problems," *Knowledge-Based Systems*, Vol. 96, 2016, pp. 120-133.
33. D. E. Goldberg, *Genetic Algorithm in Search*, *Optimization and Machine Learning*, Addison-Wesley, NY, 1989.

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