Energy Efficient Optimal Sink Placement in Wireless Sensor Network

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Abstract: Minimizing energy consumption and maximizing network lifetime are two important challenges in battery operated Wireless Sensor Networks (WSNs). Sensor nodes sense the environment periodically and forward the collected data to a sink. In a single sink WSNs, nodes closer to the sink become overburdened for relaying excessive data. This may incur faster energy consumption by nodes and lead an energy hole around the sink. As a result, the network lifetime is shortened. Multiple sinks mitigate this problem, reduce energy consumption at nodes and prolong the network lifetime by distributing the traffic over multiple sinks. In previous paper, propose multiple sink placement strategies, introduce a lifetime-oriented approach (LOA) to maximize the average network lifetime and an energy-oriented approach (EOA) to minimize the average energy consumption of sensor network. In EEMSP (Energy efficient multiple sink placement) algorithm, problem of placement of multiple sinks. In this paper, we propose a particle swarm optimization (PSO) based algorithm for placement of multiple sink in WSNs. The performances of proposed system is evaluated and compared with previous approach EEMSP combination of LOA and EOA with the random sink placement (RSP) policy under various network scenarios. The experimental results show that the proposed algorithms prolong the average network lifetime and minimize the average energy consumption than LOA, EOA, and RSP.

Keywords: WSN, Multiple sinks, PSO, RSP, EOA, LOA, Energy consumption, Network lifetime.

I. INTRODUCTION

Wireless sensor networks (WSNs) consist of hundreds to thousands number of resource constraint sensors which have the capability to sense and monitor the region where they are deployed [1]. WSNs have drawn a significant attention in recent years in many applications, e.g., health care monitoring, disaster management, environment monitoring, object tracking, etc. One of the primary concerns of the sensor network is to minimize the energy usage of sensor nodes since sensors are often batteries operated. These batteries are difficult to replace or recharge when they are deployed in hostile environment or remote location. Unwanted energy consumption reduces the operational lifetime of a sensor and the network may be partitioned. Therefore, sensor energy should be utilized efficiently for prolonging the lifetime of the node as well as the network. Multi-hop communication reduces the energy dissipation at the nodes by minimizing the transmission energy cost. In [2], the authors introduced a dynamic routing technique for multihop wireless networks to minimize the energy burden at wireless node. In the cited approach, the authors focused on the wireless networks with a single sink. Here, the sink is responsible for gathering, analyzing, and forwarding the processed data to the cloud storage [16]. The placement of sink to collect the important data from the sensors impacts the network performance significantly. In [3], the authors proposed a single sink placement strategy, both in single and multi-hop WSNs to enhance the network lifetime. In a single sink WSNs, nodes nearer to the sink forward high volume data traffic, deplete energy faster than the nodes which are away from the sink.

This may lead uneven energy depletion among the nodes, and the network becomes disconnected soon. The unbalanced energy consumption does not only shorten the network lifetime, but also increases the network latency, number of retransmissions simultaneously. Under this paradigm, it is sensible to place multiple sinks to improve the network performance. In multiple sink WSNs, energy consumption is reduced, latency is minimized and the lifetime of the network is prolonged [11]. However, the optimal sink placement is NP hard problem [15]. Several heuristics [8, 9] and meta heuristics [14, 15] approaches have been developed in the literature to address this problem.

II. RELATED WORK

In this section, we discuss some multiple sink placement techniques in WSNs, which are conceptually related to our work. The general sink placement problem is NP-Hard, so finding the optimal location of sink is very difficult [7]. Some well-known approaches such as linear integer programming, exhaustive search, iterative clustering have already been proposed in the literature to find the sink locations.

In [4], the authors proposed Geographic Sink Placement (GSP) strategy to minimize the maximum delay in WSNs. In GSP, sinks are placed at the center of gravity of a sector of a circle. GSP uses the radius of field and number of sensors to calculate the center of gravity. Intelligent Sink Placement (ISP) [4] finds the optimal sink locations from candidate locations to minimize the worst case delay. ISP utilizes the number of sensors, their location, transmission range and the number of sinks to get the optimal locations.

Authors in [5] introduced multiple constrained based sink placement techniques. The authors claimed that well-known □-means algorithm can be used to place the sinks and the final centroids can be chosen as the optimal placement. In [6] and [7], the authors proposed multiple sink placement with and without the location information in WSNs. The objective of their work is to lower the communication and computation overhead. In [8], the authors introduced two sink placement algorithms in order to minimize the deployment cost, while ensuring that each sensor is at least double covered by the sinks. Algorithm in [9] tries to maximize the network lifetime by finding the optimal number of sinks and their location. In [9], sinks are chosen greedily such that each sink can cover as many as sensors and the hop distance between the sensor and the sink is not more than the given number of hops. Some recent works also focus on the sink placement to get the optimal energy consumption. In [10], the authors concentrated on multiple sink, single hop routing through energy balancing.

Two sink placement strategies have been developed in [12] to improve the network lifetime. In [12], the sinks are placed in the region where the node density is maximized. An experience based sink placement algorithm was proposed in [13] to reduce the sink overloading. The scheme [13] gathers the information of the sensor node density in a region at different times and based on this information, it finds the candidate sink locations.

Meta heuristic approaches are popularly used in recent years for the placement of multiple sink in WSNs. In [14] and [15], particle swarm optimization (PSO) based multiple sink placement algorithm was proposed to prolong the network lifetime. Authors, in [14], used discrete PSO (DPSO) and local search together for solving the sink placement problem. However, authors [15] considered both the Euclidian distance and hop count from the gateways to the sinks for placing the sinks.

In [17], author propose two multiple sink placement strategies in WSNs which select the potential sink locations with an iterative manner. In our work, data generated by the sensors are moved to the cloud computing environment via multiple sinks. We introduce a lifetime oriented approach (LOA) to maximize the average network lifetime and an energy oriented approach (EOA) to minimize the average energy consumption of sensor network. We take into account distance from the nodes to the sinks, residual energy level and energy load of nodes to find the potential sink locations from a set of given locations. Instead of selecting the sink locations randomly, we use a local search technique to get the potential sink locations. Our algorithm proceeds iteratively and after a finite number of iterations, it produces the result which maximizes the average network lifetime (in lifetime oriented approach) and minimizes the average energy consumption (in energy oriented approach).

III. PROPOSED SYSTEM

In this paper, we propose a particle swarm optimization (PSO) based optimal sink placement (PSO-OSP) algorithm for placement of multiple sink in WSNs represented in figure 1. The algorithm is developed with an efficient scheme of particle encoding and novel fitness function. For the energy efficiency scheme of particle encoding and novel fitness function. For the energy efficiency of the proposed system, we consider various parameters such as Euclidian distance and hop count from the gateways to the sinks. The algorithm by varying the number of gateways and sensor nodes and the results are analyzed to show the efficiency of the proposed algorithm.

PSO consists of a predefined number of particles say NP, called swarm. Each particle provides a potential solution. A particle P_i, $1<=i<=N_p$ has position $X_{i,d}$ and velocity $V_{i,d}$, $1<=d<=D$ in the d^{th} dimension of the search space. The dimension D is same for all paricles. A fitness function is used to evaluate each particle for verifying the quality of the solution. In the initialization process of PSO, each particle is assigned with a random position and velocity to move in the search space. During each iteration, each particle finds its own best, personal best called $Pbest_i$ and the global best called Gbest. To reach the global best solution, it uses its personal and global best to update the velocity $V_{i,d}$ and position $X_{i,d}$ using the following equations

$$V_{i,d}(t+1) = \omega \times V_{i,d}(t) + c_1 \times \boldsymbol{\chi_1} \times \left(X_{Pbest_{i,d}} - X_{i,d}\right) + c_2 \times \boldsymbol{\chi_2} \times \left(X_{Gbest_d} - X_{i,d}\right) \ldots (1)$$

$$X_{i,d}(t+1) = X_{i,d}(t) + V_{i,d}(t+1) \ldots\ldots (2)$$

Where $0 < \omega < 1$ is the inertia weight, $c_1, c_2, 0 \le c_1, c_2 \le 2$ are the acceleration coefficients and $\chi_1, \chi_2, 0 < \chi_1, \chi_2 < 1$ are the randomly generated values. The updating process is repeated until it is reached to an acceptable value of $Gbest$. After getting new updated position, the particle evaluates the fitness function and updates $Pbest_i$ as well as $Gbest$ as follows

$Pbest_i = P_i$, if ($Fitness(P_i) < Fitness(Pbest_i)$)
$Pbest_i$, otherwise
$Gbest = Pbest_i$, if ($Fitness(Pbest_i) < Fitness(Gbest)$)
$Gbest$, otherwise

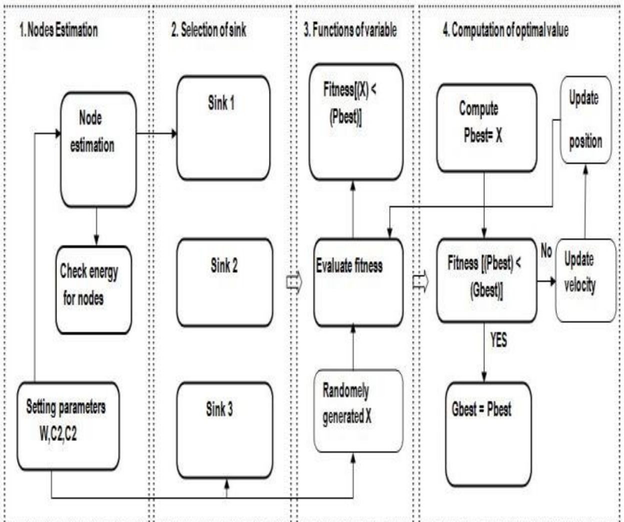

Figure1: Update of multiple sink selection framework

Particle representation and initialization:
In PSO, a particle represents a complete solution. For multiple-sink placement of the proposed algorithm, it represents optimal positions of the sinks with respect to the gateway nodes.
Let $P_i = [X_{i,1}(t), X_{i,2}(t), X_{i,3}(t), \ldots X_{i,D}(t)]$ be the i^{th} particle of the population where each component $X_{i,d}(t) = (x_{id(t)}, y_{id}(t))$, $1<=i<=N_p$, $1<=d<=D$, denotes the coordinates of the sink nodes. Then the i^{th} particle can be represented as follows

$P_i = [(x_{i1}(t), y_{i1}(t)), (x_{i2}(t), y_{i2}(t)), (x_{i3}(t), y_{i3}(t)), \ldots\ldots, (x_{id}(t), y_{id}(t))]$
Where N_p denotes the swarm of particles and D represents the number of sinks are supposed to be placed.

Algorithm:

Input: set of gateway nodes: $G=\{g_1,g_2,g_3,\ldots,g_m\}$; predefined swarm size : N_p
Number of dimensions of a particle: D=l
Output: optimal positions of sink nodes $SN = \{SN_1\ SN_2\ SN_3 \ldots, SN_l\}$

Step1: initialize particles P_i, i.j , $1<=i<=N_p$, $1<=j<=D=l$, number of SNs
$X_{i,j}(0) = (x_{i,j}(0), y_{i,j}(0))$ /* deployed positions of sink */
Step2: for i=1 to N_p do
2.1 calculate fitness(P_i)
2.2 $Pbest_i = P_i$
End for
Step3: $Gbest = \{Pbest_k / Fitness(Pbest_k) = \min(Fitness(Pbest_i)), 1<=i<=N_p)\}$
Step4: for t=1 to Terminate /*Terminate = Max.number of iterations */
For i=1 to N_p do
4.1 Update velocity and position of P_i using eqs (1),(2)
4.2 Calculate Fitness (P_i)
4.3 if Fitness(P_i) < Fitness($Pbest_i$) then
$Pbest_i = P_i$
End if
4.4 if Fitness ($Pbest_i$) < Fitness(Gbest)
$Gbest = Pbest_i$
End if
End for
End for
End for
Step 5: stop

IV. Result and discussion

Our experiments are conducted using the NS-2.34 simulator. We conduct the experiments in two steps. The initial step is to check the viability of our plan, and then deeper study is investigation is done to assess the delay and throughput in more detail.

In the first step, there are 43 mobile nodes in the network, and communication starts from source to destination. Here hop to hop communication occurs and we can calculate the distance based on position of an individual node. The individual communication between user to user, numbers of data flows measured. None of the individual traffic rate goes beyond a certain threshold, but the sum of them does. Here we can know the transmission rate of every node based on residual energy. In our work, we can take multiple sinks for receiving the data and using our algorithm based on that best optimal path selection for sink placement. The best placement of sink can be helpful to more data can receive the data.
The connections among mobile nodes are UDP connections, and we send CBR (Constant Bit Rate) traffic in each communication channel. The CBR rate of the connections is 512Kb/s. The size of the scenario field is 1000m x 1000m. The routing protocol we use is a revised AODV routing protocol that integrates our PSO-OSP, EEMSP, and RSP methods.

Table1: Simulation table

PARAMETER	VALUE
Application traffic	CBR
Transmission rate	1000 bytes/0.01ms
Radio range	250m
Packet size	1000 bytes
Channel data rate	2Mbps
Maximum speed	25m/s
Simulation time	10secs
Number of nodes	43
Area	1000x1000
Routing protocol	AODV
Routing methods	RSP, EEMSP, PSO-OSP

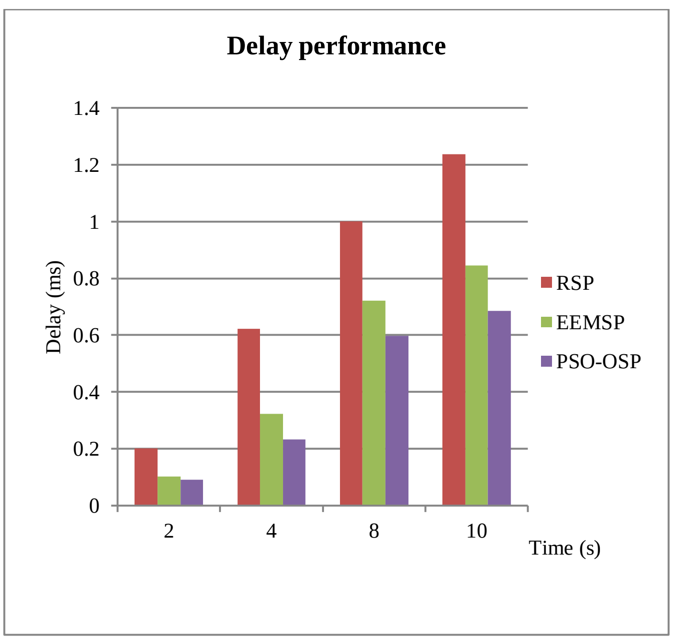

Figure2: Delay Performance

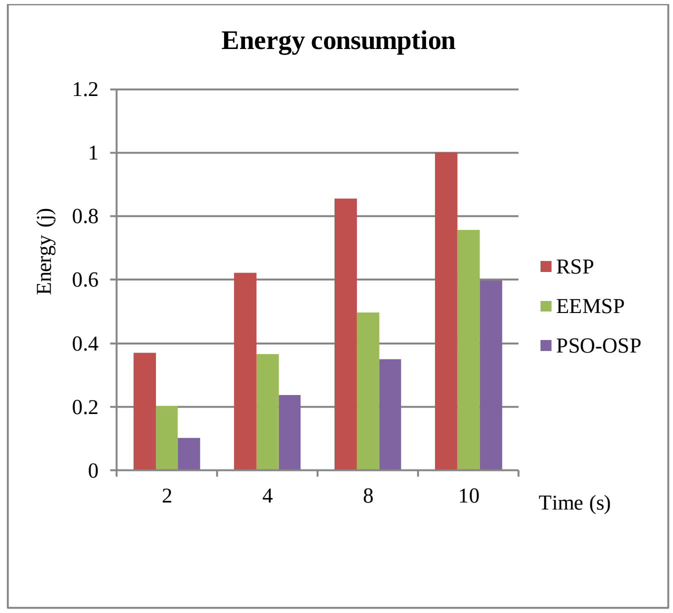

Figure3: Energy Consumption

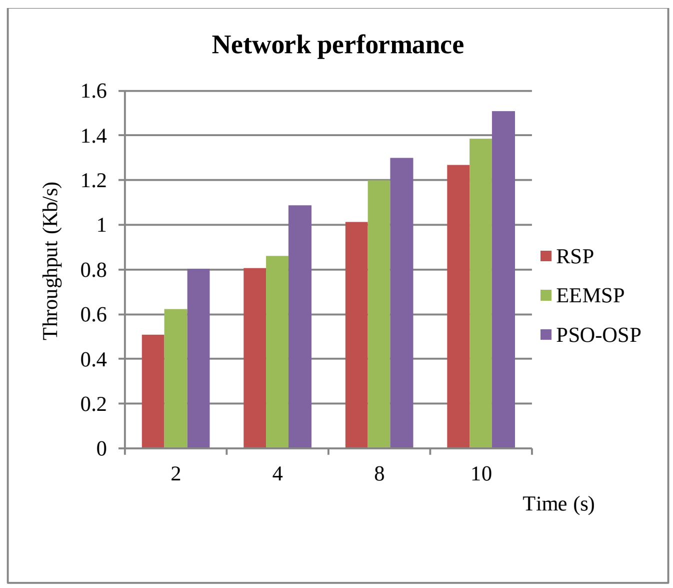

Figure4: Throughput

Figure 2 represented as End to End Delay, and it can be depends on time to vary the output. The performance of the PSO-OSP improves delay time it means decrease the delay between communication nodes compare to EEMSP approach and random sink placement method (RSP).

Figure3 presented as Energy consumption, and it can be depends on time to vary the output. The performance of the PSO-OSP improves energy levels it means reduce the energy consumption at every node level compare to EEMSP approach and random sink placement method (RSP).

Figure4 represented as Throughput, and it can be depends on time to vary the output. The performance of the PSO-OSP improves the throughput compare to EEMSP approach and random sink placement method (RSP).

Conclusion:

In this paper, we have proposed (PSO-OSP) multiple-sink placement algorithm based on PSO using efficient particle representation and fitness function. For the energy efficiency of the proposed algorithm, we have considered the Euclidian distance and hop count. The objective of our PSO based sink placement approach is to improve the network lifetime with efficient energy levels to maintain in network. The proposed algorithms are simulated and compared with the EEMSP approach and random sink placement algorithm (RSP) with respect to various performance metrics. To show the improvement of PSO-OSP with an existed exhaustive grid search algorithm, we have calculated network lifetime. It can be observed that the PSO-OSP out performs the existed algorithms.

References

[1] I.F. Akyildiz, W.Su, Y.Sankarasubramaniam, and E.Cayirci, "Wireless sensor networks: A survey," Computer Networks, vol. 38, pp. 393-422, March 2002.

[2] S.Bhattacharjee, and S.Bandyapodhyay, "Lifetime maximizing dynamic energy efficient routing protocol for multihop wireless networks," Simulation Modelling Practice and Theory, vol. 32, pp. 15-29, 2013.

[3] F.Chen, and R. Li, "Sink node placement strategies for wireless sensor networks," Wireless Personal Communications, vol. 68, pp. 1-17,2013.

[4] W.Y.Poe, and J.B. Schmitt, "Minimizing the maximum delay in wireless sensor networks by intelligent sink placement," Distributed Computer Systems Lab, University of kaiserslautern, Technical Report No. 362/07, pp 1-20.

[5] J. Flathagen, O.Kure, and P.E.Engelstad, "Constrained-based multiple sink placement for wireless sensor networks", in:Proceedings of 8th IEEE International Conference on Mobile Ad hoc and Sensor Systems (MASS), 2011.

[6] W.Y.Poe, and J.B. Schmitt, "Self-organized sink placement in large scale wireless sensor networks," in: Proceedings of IEEE International Symposium on Modeling, Analysis and Simulation of Computer and Telecommunication Systems (MASCOTS), 2009.

[7] W.Y.Poe, and J.B. Schmitt, "Sink placement without location information in large scale wireless sensor networks," in:Proceedings of Asian Internet Engineering Conference (AINTEC),2009.

[8] L.Sitanayah, K.N.Brown, and C.J.Sreenan, " Multiple sink and relay placement in wireless sensor networks," in:Proceedings of the 1st Workshop Artificial Intelligence for Telecommunications and Sensor Networks, 20th European Conference on Artificial Intelligence, 2012.

[9] X.Xu, and W.Liang, "Placing optimal number of sinks in sensor networks for network lifetime maximization," in:Proceedings of IEEE International Conference on Communications (ICC), 2011.

[10] T.P.Jain, D.S.Saini, and V. Bhooshan, "Lifetime optimization of a multiple sink wireless sensor network through energy balancing," Journal of Sensors, Volume 2015,pp.1-6,2015

[11] P.Chatterjee, and N.Das, "Multiple sink deployment in multi hop wireless sensor networks to enhance lifetime," in:Proceedings of IEEE International Conference on Applications and Innovations in Mobile Computing (AIMoC), 2015.

[12] D.Das, Z.Rehana, S.Roy , and N.Mukherjee, " Multiple sink placement strategies in wireless sensor networks," in:Proceedings of International Conference on Communication Systems and Networks (COMSNETS), 2013.

[13] S.Banerjee, S.S.Bhunia, and N.Mukherjee, "Experience based sink placement in mobile wireless sensor networks," in: Proceedings of 15th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing (CCGrid), 2015.

[14] H. Safa, W. El-Hajj, and H. Zoubian, "Particle swarm optimization based approach to solve the multiple sink placement problem in WSNs," in: Proceedings of IEEE International Conference on Communications (ICC), 2012.

[15] C.S.Rao, H.Bank, and P.K.Jana, "PSO-based multiple sink placement algorithm for protracting the lifetime of wireless sensor networks," in:Proceedings of 2nd International Conference on Computer and Communication Technologies, 2016.

[16] S.Mao, "Crowd cloud routing based on opportunistic computing for wireless sensor networks," EURASIP Journal on Embedded Systems, vol. 2016, pp. 25 , 2016.

[17] Bhattacharjee, Sanghita & Agarwal, Kavisha. (2017). Energy efficient multiple sink placement in wireless sensor networks. 1-7. 10.1109/NSYSS2.2017.8267787.