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Energy Efficient EMO Algorithm Based Scheduling Technique in Wireless Sensor Networks

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Abstract: In Wireless Sensor Networks (WSNs), the major problem in multiple sinks is efficient data collection and scheduling which can be overcome by aggregated tree construction and TDMA based scheduling technique. Earlier, the techniques used for aggregated tree construction process takes more iteration to complete entire process which maximizes the scheduling delay. Therefore, there is need of an efficient aggregated tree construction which reduces the wastage of iteration time. In this study, we propose energy Efficient Multi-swarm fruit fly Optimization (EMO) algorithm for scheduling. In our EMO, the multi-swarm fruit fly optimization technique is applied in Pocket Driven Trajectories (PDT) to minimize the delay and save energy. Then Breadth First Search (BFS) algorithm is used for time slot scheduling process. The proposed EMO algorithm reduces the iteration time to maximize the aggregated tree construction speed. The simulations show that the proposed EMO algorithm significantly reduces the data collection delay and energy consumption.

Key words: Time Division Multiple Access (TDMA), Pocket Driven Trajectories (PDT), Breadth First Search (BFS), aggregated tree, scheduling, data collection

INTRODUCTION

A Wireless Sensor Network (WSN) comprises a group of small radio-enabled sensing devices in geographical area for processing and sensing the data and for providing communication among the sensor nodes. WSN is used in application such as battlefield, emergency relief, patient health monitoring using biomedical sensors, environment monitoring and so, forth (Chen *et al*., 2009a, b; Wang and Deshpande, 2008; Li and shatz, 2010; Li *et al*., 2013; Chilamkurti *et al*., 2009; Yao *et al*., 2015). The number of sensor nodes ranges from a few hundred to several thousands. These nodes enable communication among them via. a wireless medium and perform collaborative data processing with distributed sensing. The power of the networks is defined as the ability to deploy large numbers of tiny nodes that are adaptable and self-manageable with limited computations, sensing environment and wireless communication (Javed *et al*., 2012; Han *et al*., 2013). Owing to the limited battery resources on each node, the data extracted from a sensor network is difficult although, WSN provides new data sources for a wide application (Sheng *et al*., 2013; Xiao *et al*., 2012; Yao *et al*., 2015; Sengupta *et al*., 2012).

In WSN, data collection is performed for gathering sensing data from the sensor nodes to certain sink nodes and for analyzing the collected data (Chen *et al*., 2009a, b). Efficient data collection plays a significant role in power conservation (Wei *et al*., 2011; Chu *et al*., 2006; Li *et al*., 2010). While designing an energy-efficient data collection protocol, we must consider some challenges in WSN. They are as follows: the strong spatio-temporal correlations in most WSNs must be effectively exploited and the routing plan for data movement must be optimized. The data generated in sensor node in most sensor network deployments (in case of environmental monitoring) is highly correlated in time (future values are correlated with current values) and space (two colocated sensors are strongly correlated). By prior domain knowledge or by historical data traces, these correlations are captured by the predictive model constructions. These correlations are optimally exploited very hard due to the distributed nature of data generation and sensor node's resource-constrained nature (Liu *et al*., 2015; Wang and Deshpande, 2008). In WSN, the issues while collecting data are as follows.

Sensor nodes cannot run sophisticated data compression algorithms as it has limited memories and is computationally constrained (Xu *et al*., 2015; Nittel *et al*., 2005).

As WSN communicate in a broadcast manner all nodes within the radio range can receive the message on transmitting a message by a node (Wang and Deshpande, 2008).

Since, there is more consumption of energy during wireless medium communication, data transmission back to a central node for offline storage, querying and data

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analysis becomes expensive in case of non-trivial size WSNs. This can reduce the processing time, thereby improving the result accuracy and energy efficiency (Nittel *et al*., 2005).

Problem identification: In most sensor network deployment the sensor node initiated data is mainly used in environmental monitoring applications is extremely correlated both in time (future values correlated with current values) and in space (Liu *et al*., 2015). In wireless networks, the data collection has a challenge of radio interferences which intercepts packet transmission of nearby sensor nodes concurrently. In data collection, scheduling data transmissions is done by ignoring such inferences result in significant delay. In wireless sensor networks Multiple-Sink data collection problems (Kulik *et al*., 2008) transmits a large amount of data to one of multiple data sinks that c an be terminated by the design of Linear Programming (LP) based approximation algorithm (ISI., 1989) which reduces the data collection schedule latency and provide a constant-factor production guarantee. In addition, a heuristic algorithm (Chen *et al*., 2009a, b) derived from breadth first search was presented for this problem. The approximation algorithm outperforms the heuristic upto 60% and evaluated using simulation. However, it requires more iteration in approximation algorithm as well as in heuristic algorithm leading to increased time.

Pockets are referred as a set of participating nodes formed by one or more geographically clustered sets. Pocket Driven Trajectories (PDT) (Kulik *et al*., 2008) algorithm used for optimizes the data collection paths by PDT algorithm reduces the number of non-selected nodes by spatially restricting the aggregation path to a corridor that connects the pockets in an energy efficient manner in the data collection structure (Kulik *et al*., 2008). But too PDT fails to preserve iteration time in data collection process which reduces scheduling speed when compared to Data Collection by grouping the sensors in Aggregation Zones (DCAZ) (Cano *et al*., 2008), Joint Frequency Time Slot Scheduling (JFTSS) (Incel *et al*., 2012; Li *et al*., 2015) and Naive Query Processing (NQP) (Madden *et al*., 2002) approach. To address the above issues in this study an energy Efficient Multi-swarm fruit fly Optimization (EMO) is combined along with PDT algorithm to optimize aggregated tree that reduces the iteration time. Then using Breadth First Search (BFS) (Cano *et al*., 2008) each empty time slot is searched to perform time slot allocation process.

Literature review: Sengupta *et al*. (2012) have proposed a Pocket-Driven Trajectories algorithm for optimizing the paths used for data collection by approximating the global minimal Steiner tree using local spatial knowledge. They identified the spatial factors responsible for efficient data collection. Some of the factors are the location and dispersion of the data clusters, the distribution of participating nodes over the network, the location and size of communication holes and the location of the sink that issues a query. To measure the efficiency of all algorithms, a near-optimal solution that is globally approximated minimal Steiner tree is computed. However, the variation in the physical conditions for the sensed environment may cause variations in node participation.

Li *et al*. (2015) have proposed an efficient way for performing data collection by grouping the sensors in aggregation zones, thereby allowing the aggregators to process the generated data inside the aggregation zone. This can be performed for reducing the amount of transmissions to the sink. Moreover, a security mechanism has been used based on hash chains for securing data transmissions in networks with low-capability sensors and without any need for an instantaneous source authentication. However, the total load of the network increases while providing security.

Chen *et al*. (2009a, b) have proposed an approximation algorithm for reducing the latency caused during data collection schedule. They also showed that this algorithm provides a constant-factor performance guarantee. Based on breadth first search, a Heuristic algorithm has been presented. They evaluated the performance of these two algorithms. Finally, they showed that the approximation algorithm outperforms the heuristic up to 60%.

Li *et al*. (2015) have observed that the node-based (RBCA) and link-based (JFTSS) channel assignment schemes are efficient in terms of eliminating interference when compared with allocating different channels on different branches of tree (TMCP). Eliminating interference completely proved that the achievable schedule length is lower bounded with the help of half-duplex radios by max (2nk-1, N) for raw-data converge cast and by maximum degree in the routing tree for aggregated converge cast. By optimal converge cast scheduling algorithms, it is shown that lower bounds are achievable using appropriate routing algorithms. However, in case of dense deployments, a single transmitter can jam others due to their small internode distances and higher level of interference.

Liu *et al*. (2015) have presented coordinated query processing mechanisms in order to handle mobile generated remote queries in mobile sensor multitier heterogeneous networks. They discussed three approaches such as a Naive Query Processing approach (NQP) and two Coordinated Query Processing mechanisms (CQP-1 and 2). However, the percentage of query injection decreases while increasing the workload, since, query generation rate increases when the number of members in each group increases.

MATERIALS AND METHODS

Network model: In this study, an energy efficient multi-swarm fruit fly optimization combined PDT algorithm is proposed (EMO). An aggregated tree is extended for multiple sinks in absence of high energy dissipation. Create path on each tree bonds using separate sinks. This path maximizes the use of involved nodes in the tree and conversely minimizes the number of iterations. In efficient data collections a number of spatial factors are recognized as distribution of involved nodes over the networks, the location and dispersion of the data clusters, the location of the sink preceding a query as well as the placement and size of communication holes.

TDMA scheduling is used for fast time slot allocation which an eliminate collisions and retransmissions. The BFS time slot assignment algorithm is applied over each PDT towards the multiple sinks and a lower bound will be determined for the schedule length. The network model of proposed design is shown in Fig. 1.

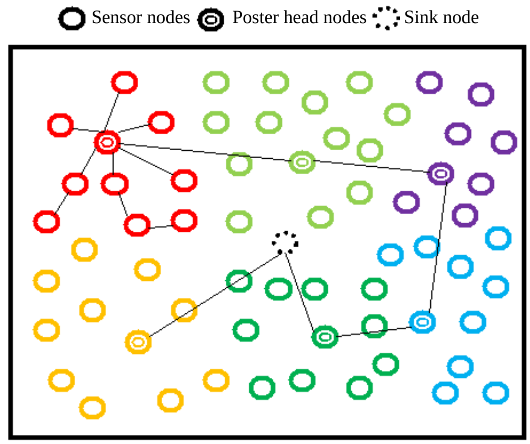

Fig. 1: Network model of our proposed work

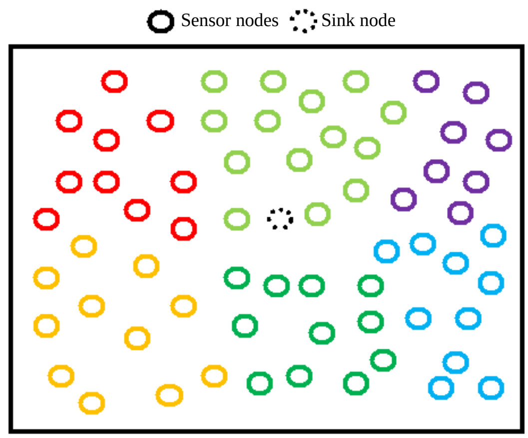

Fig. 2: Pocket formation

Energy efficient tree aggregation technique: In tiny aggregations from a powered, storage-rich base station, users masquerade aggregation queries. Through piggybacking on the offered ad hoc networking protocol, query-executing operators are disseminated into the network. Sensors sent the data towards the user using routing tree entrenched at the base station. Based on aggregation function and value-based partitioning indicated in the query, data are aggregated. For example, take a query that calculates the number of nodes in imprecise-sized network. First, insert the request to calculation into the network. Every leaf node under the tree then informs a count of 1 to their parent. After that the internal nodes add the count of their children, then add 1 to it and state that value to their parent. In this mode, counts broadcast up the tree and out at the root.

Pocket formation using PDT algorithm: PDT algorithm is based on spatial correlation in sensor values joined with query perspicacity outcome in a set of contributing nodes created by one or more geographically clustered set. These geographically clustered set are called Pockets P (Li *et al*., 2015). The squared remoteness between two vectors in multidimensional space is the summation of squared differences in their coordinates and multidimensional distance is known as Euclidean distance. Mathematically, the Euclidean distance between two vector p, q in N dimension can be compute as follows:

$$D_{p,\,q} = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \quad (1)$$

Where:

p and q = The distance vectors
n = No. of dimensions in the network

Based on the distance of base station and each node in the system are grouped to create pockets in the given network and the pocket formation process is shown in Fig. 2.

Pocket head selection using Multi-Swarm fruit fly Optimization algorithm: The osphresis organs of fruit fly can find all kinds of scents floating in the air, it can even smell food source from 40 km away. Then, after it gets close to the food location, it can also use its sensitive vision to find food and the company's flocking location and fly towards that direction too (Yuan *et al*., 2014). When a fly decides to go for hunting, it will fly randomly to find the location guided by a particular odor. While searching, a fly also sends and receives information from its neighbors and makes comparison about the so far best location and fitness (Yuan *et al*., 2014). If a fly has found its favorable spot, it will then identify the fitness by taste. If the location no longer exists or the taste is 'bitter', the fly will go off searching again. The fly will stay around at the most profitable area, sending, receiving and comparing information with its swarm at the same time (Yuan *et al*., 2014).

Based on the food finding characteristics of swarm fruit fly swarm although, the swarm inspired by swarm behavior of fruit fly and the implement procedure of swarm fruit fly is less complex one. The multi-swarm fruit fly structure is modified by include crossover with osphresis operation. The proposed EMO algorithm starts with initialization step that arrange the swarm locations and generate random number of Populations (P_1). The control values are as follows:

$$\xi_y = \xi_y^{min} + rand(0, 1) \times \left(\xi_y^{max} - \xi_y^{min}\right) \; y = 1, 2, \ldots, n \tag{2}$$

Where:

n = No. of control variables

ξ_y^{min} and ξ_y^{max} = Minimum and maximum limits of control variable

After define control values and limits, perform the first set generation, here to perform operations on randomly generated population vector to get Best Population Vector ($Best_{PV}$). The random operations such as osphresis foraging and crossover is performed each iteration in full module. In osphresis foraging operation, food sources of the population P_1 are generated randomly around the current fruit fly swarm Locations (L). The location of swarms are not fixed one L_Δ is set of the randomly initialized swarm location as follows:

$$L_\Delta = \left(\xi_1, \xi_2, \ldots, \xi_n\right) \tag{3}$$

Consider the generated food sources S_1, S_2, ..., S_{pl} and the search space as follows:

$$s_{xy} = \xi_y \pm rand(0, 1) \; y = 1, 2, \ldots, n \tag{4}$$

In osphresis foraging food sources generated around its swarm location within a radius equals to one. This radius is fixed and cannot be changed during iterations. For optimal solution this search region is too small and considerable increase needed in iterations. Hence, search radius can be changed dynamically with iteration number:

$$\lambda = \lambda_{max} \times \exp\left[\log\left(\frac{\lambda_{min}}{\lambda_{max}}\right) \times \frac{I_c}{I_{max}}\right] \tag{5}$$

Crossover is an efficient recombination operator has been used to search swarm food location in certain long range. But by recombination crossover, new swarm locations are generated using the following crossover Eq. 6:

$$\begin{aligned} & s_{xy} = (1-\lambda) \times s(1, y) + \lambda \times s(x, y) \\ & x = 1, 2, \ldots, P_t \text{ and } y = 1, 2, \ldots, n \end{aligned} \tag{6}$$

New control variables are used for computation of total number of food sources whose limits have to be checked, new population vector is obtained and its fitness vector is evaluated. In vision foraging phase, compute Best food source Location ($Best_L$) with lowest fitness was given as follows:

$$Best_L = \arg\left(\min\left(all_{L_x}\right)\right) \; x = 1, 2, \ldots, P_t \tag{7}$$

Only if the computed Best Location ($Best_L$) is superior to the current fruit fly swarm location, swarm location will move on to the new position. Otherwise, swarm location will not change.

If the maximum number of generations is reached, the process stops. Or else move to the control variable calculation step and repeat the process up to the defined maximum number of generations. EMO algorithm used to compute the best value among collection of values using following fitness metrics. In each node of the Pocket, we notice varying attributes such as packet delivery/loss ratio, energy consumption, packet overhead, bandwidth and throughput. Best optimized value of each attributes is computed from our proposed EMO algorithm.

Packet delivery/loss ratio: Let us assume that the average number of packets sent from one node to another node for forwarding process is marked as N_{sent} and the average number of valid data received from one end is marked as $N_{received}$:

$$X = \frac{N_{ssent}}{N_{received}} \tag{8}$$

During the transmission of packets to the value is updated at each node corresponding to its neighboring node. After establishing the route from the source to the destination at each node the trust value is calculated for its neighboring node. Based on the number of packets forwarded and number of packets forwarded without tampering, the ratio model as follows:

$$R = P_F\left(1-\frac{1}{r}\right)+P_{WT}\left(1-\frac{1}{r}\right) \quad (9)$$

where, r is the packet rate, for example, if packet rate is 10 packets/sec and the number of packets forwarded $P_F = 7$ packets and number of packets forwarded without tampering $P_{WT} = 7$ packets. the obtained delivery and loss ratio is 2.9.

Energy model: The energy consumption is derived from basic energy model by Heinzelman *et al*. (2000) which examine both the transmitter and receiver part energy requirements. The energy consumption of wireless node depends on the amount of the data and distance to be sent. The energy consumption of a node is proportional to square of Distance (D^2) when the propagation Distance (D) less then the threshold Distance (D_0), otherwise, it is proportional to (D^2). The total energy consumption of each node in the network for transmits and receivesbit data packet:

$$E_{total} = E_t(n, d)+E_r(n) \quad (10)$$

where, E_t (n, d) and E_t (n) are energy consumption of transmitting and receiving node:

$$E_t(n, d) = \begin{cases} n\times E_{elec}+n\times\varepsilon_{fs}\times D^2;\ \text{if } D < D_0 \\ n\times E_{elec}+n\times\varepsilon_{mp}\times D^4;\ \text{if } D \geq D_0 \end{cases} \quad (11)$$

$$E_r(n) = n\times E_{elec} \quad (12)$$

where, E_{elec} the energy is dissipated per bit to run the transmitter or receiver circuit, amplification energy for free space model (ε_{fs}) and for multi-path model (ε_{mp}) depends on the transmitter amplifier model D_0 is the threshold transmission distance.

Packet overhead: Ratio of the number of packets sent as a fraction of the number of packets delivered to their destination nodes in the network.

Bandwidth: The rate of data transfer, bit rate or throughput, measured in bits per second. The amount of data that can be carried from one node to another in a given time period is known as BandWidth (BW). It measures how much data can be sent over a specific connection in a given amount of time and it is derived from the Quality factor (Q):

$$Q = \frac{f_0}{f_2 - f_1} \quad (13)$$

Where:
f_0 = The center frequency
f_1 = Low cutoff frequency $f_1 = f_0\left(\sqrt{1+1/4Q^2}-1/2Q\right)$
f_2 = The high cutoff frequency $f_2 = f_0\left(\sqrt{1+1/4Q^2}-1/2Q\right)$

$$f_2 - f_1 = \frac{f_0}{Q} \quad (14)$$

Throughput: Total number of packets delivered over the total simulation time:

$$T = \frac{N}{t} \quad (15)$$

From above metrics, the fitness function of multi-swarm fruit fly optimization algorithm is described. The pocket head node maintains the condition namely maximum packet delivery, bandwidth and throughput, minimum packet loss, energy consumption and packet overhead than other nodes in the pockets. If the condition is satisfied means, the node is considering as pocket head node, otherwise its normal node. The pocket head selection process is shown in Fig. 3.

Spatially limiting aggregation path to a passageway which attaches the pockets in an energy-efficient approach, EMO algorithm reduces the number of non-selected nodes in the data collection structure. The algorithm for constructing the aggregation tree by consider a unit disk graph:

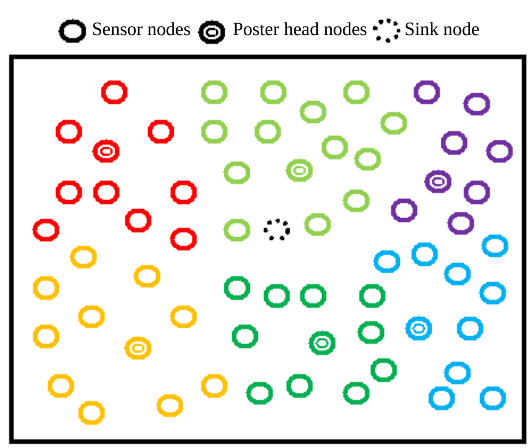

Fig. 3: Pocket head selection process

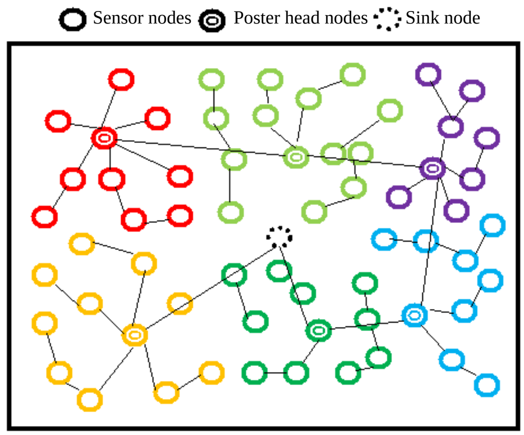

Fig. 4: Smallest spanning routing aggregated tree

$$M = (N, L)$$

Where:
N = The set of sensor nodes
L = The set of communication links

Each Query Q issued by a sink S selects a subset n of N apply EMO algorithm discover a set of pockets for a given query Align the aggregation tree to the spatially optimal path connecting these pockets. This path maximizes the use of participating nodes in the tree and conversely minimizes the number of non-participating nodes identify a number of spatial factors for efficient data collection such as distribution of participating nodes over the network. The smallest spanning routing tree with the sample network is shown in Fig. 4. When there are no interfering links, the algorithm executes $O(|\varepsilon_T|^2)$ time and play down the schedule length. The working flow of EMO algorithm is shown in Fig. 5 and algorithm steps are shown in Algorithm 1.

Time slot assignment algorithm: Here, an edge is selected in Breadth First Search (BFS) order initializing from any node in each iteration. That edge is assigned with the minimum time slot which is different from all its.neighboring edges concerning interfering constriction The working steps of BFS based slot allocation are present in Algorithm 2.

After the construction of aggregation tree the wastage of time in iteration is reduces. For this, TDMA scheduling is applied. In this process first, a lower bound on the schedule length is estimated and then a time slot assignment scheme is applied that achieves the bound. BFS time slot assignment algorithm is applied over each pocket towards the multiple sinks for assignment of time slot. In this algorithm an edge (e) is initialized from any

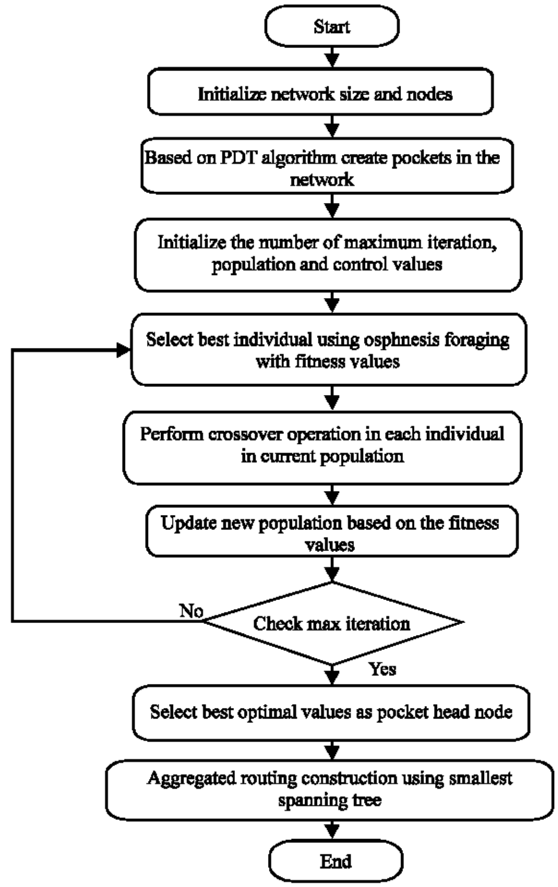

Fig. 5: Work flow of proposed EMO algorithm

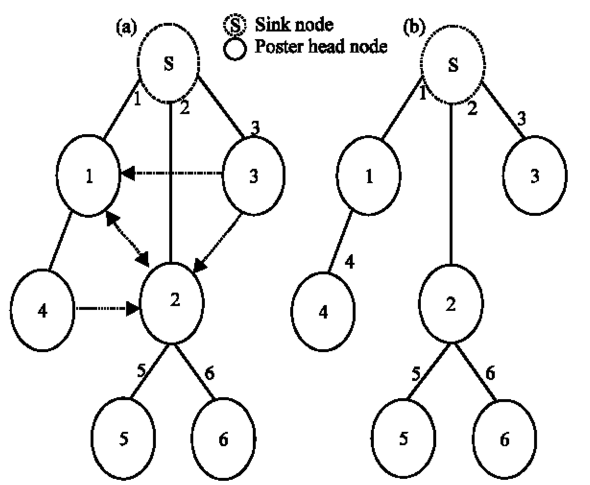

Fig. 6: Time slot scheduling: a) Aggregated time slot with convergence cost and pipeline structure and b) BSF based

node in the pocket using BFS order and the edge is allocated to the minimum time slot (Fig. 6). BFS based scheduling minimize the schedule length in the absence interfering links for each pocket and reduce the wastage time of iterations. The maximum run time of BFS is $O(|\varepsilon_T|^2)$. The aggregated time slot convergence cost and pipelining is shown in Fig. 6a and our contributions based time slot allocation is present in Fig. 6b.

Algorithm 1; Aggregating routing tree formation:
Input: Nodes (N) and links (L)
Output: Aggregated routing tree

1: Assume network with k nodes that is represented by associated unit disk graph M = (N, L) where N is the set of sensor nodes and L is the set of communication links
2: Each Query Q issued by a Sink S selects a subset n of N and start Pocket formation
3: After grouping pockets, base station gathers packet delivery, loss, energy consumption, packet overhead, bandwidth and throughout and those are optimized by EMO technique
4: Frame the rule: Max (packet delivery, bandwidth and throughput), Min (packet loss, overhead and energy consumption
5: If the node satisfy above conditions, the node consider as pocket head
6: The sink calculates an inclusive graph based on the EMO results and the base station aligns the routing tree based on the smallest spanning tree path based on the Pocket head strength

Algorithm 2; Time slot scheduling:
Input: Packet Head (PH) and edges (e)
Output: Compute time slot needed edge (e)

1: Initialize the number of Pocket Head node (PHs) and corresponding edges
2: Check edge slot condition
3: If the edge is not free compute next free edge from all edge details $s\varepsilon_T$ based on breadth first search algorithm
4: Allocate lowest time slot to the slot free edge (e) regarding neighboring and interfering constricts and update the all edge detail by $\varepsilon_T \leftarrow \varepsilon T \setminus \{e\}$
5: Repeat step 2-4 until complete scheduling, the maximum round is $O(|\varepsilon_T|^2)$

RESULTS AND DISCUSSION

Simulation model and parameters: The Network Simulator (NS2) (ISI., 1989) Version 2.32 is used to simulate the proposed architecture. In the simulation, 100 mobile nodes move in a 500×500 m region for 50 sec of simulation time. All nodes have the same transmission range of 250 m. The simulated traffic is Constant Bit Rate (CBR) (Table 1).

Table 1: Simulation settings and parameters

Parameters	Values
No. of nodes	50
Area size	500×500
Mac	IEEE 802.11
Transmission range	250 m
Simulation time	50 sec
Traffic source	CBR
Packet size	512
Initial energy	20.1 J
Receiving power	0.395
Transmission power	0.660
Rate	50, 100, 150, 200 and 250 kB

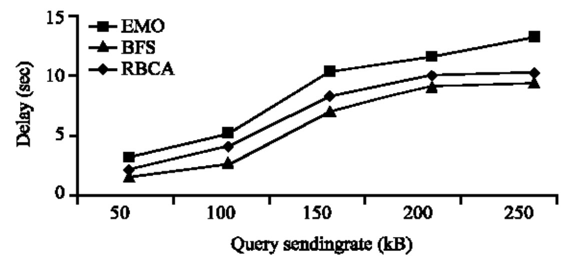

Fig. 7: Rate vs. delay

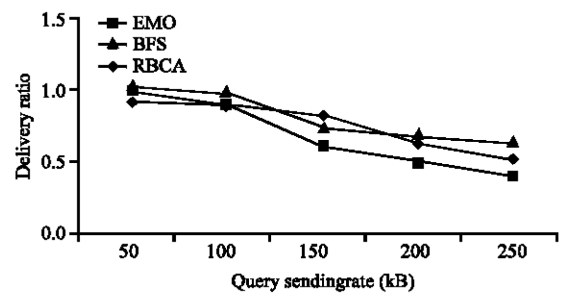

Fig. 8: Rate vs. delivery ratio

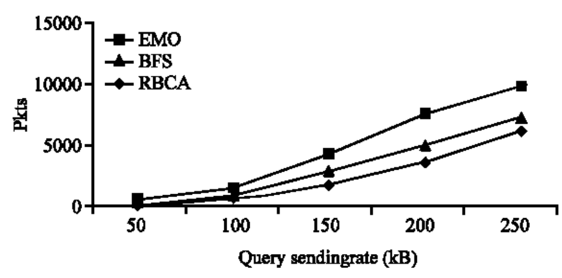

Fig. 9: Rate vs. drop

Performance metrics: The proposed energy efficient EMO algorithm based scheduling technique (EMO) is compared with Greedy BFS technique (Xiao *et al*., 2012) and Receiver Based Channel Assignment (RBCA) (Yao *et al*., 2015). The data generation rate is varied as 50, 100, 150, 200 and 250 kB and the performance is evaluated mainly, according to the following metrics: packet delivery ratio, packet drop, energy consumption and end to end delay.

Figure 7 shows the delay of all the 3 techniques for varying rate scenario. Increase in sending rate yields more packets and hence, the data collection time increases resulting in the increase of delay. But EMO has 36% lesser delay than BFS and 19% lesser delay than RBCA.

Figure 8 and 9 show the packet delivery ratio and packet drop, respectively of all the 3 techniques for different rate scenario. Since more packets are buffered in the queue, the packet drop will be more and delivery ratio

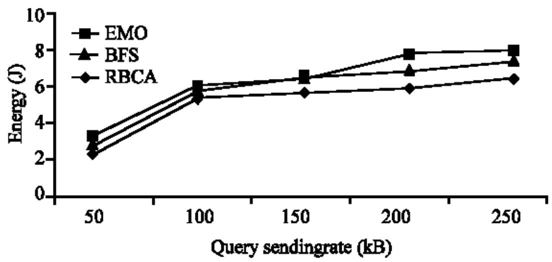

Fig. 10: Rate vs. energy consumption

will be slightly degraded which can be seen from Fig. 9 and 10. It is clear that EMO outperforms the techniques by obtaining delivery ratio 20 and 7% higher than BFS and RBCA, respectively. The corresponding packet drops for EMO is 50 and 32% lesser than these two techniques. In both the metrics, the performance of RBCA is very close to EMO.

The average energy consumption of all the 3 techniques are given in Fig. 10. The energy consumed by the nodes increases slightly when the traffic rate is increased. Figure 10, we can see that EMO has the least energy consumption followed by BFS and RBCA. It is less by 18 and 14% than these two approaches.

CONCLUSION

In this study, we proposed an EMO algorithm that can attain minimum delay and energy consumption in TDMA scheduling for multiple sink WSNs. At first, we combined energy efficient multi-swarm fruit fly optimization technique with PDT which maximizes the participating node with lessen wastage of time in iteration. Then, we continue to implement time slot allocation using BFS technique for empty slot searching process. Simulation results show that the proposed EMO algorithm remarkably reduces iteration delay and energy consumption in terms of various test scenarios.

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