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Energy-Efficient Data Aggregation Using Mobile Sinks over Wireless Sensor Networks

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Abstract

Wireless Sensor Networks can be implemented over extensive coverage areas and carry out the data aggregation process through various techniques. The performance of the network is influenced by these processes, and the mobility of sensors also imposes limitations. Numerous researchers have tackled this problem and devised different solutions to address it. This paper will present a mobile sink data aggregation method and evaluate its effectiveness using different protocols, such as LEACH and TEEN, within the limitations of a scalable network. Based on the analysis conducted through simulations, it is evident that the proposed scheme utilizing the TEEN protocol has improved the overall performance of the network when compared to LEACH. This enhancement is reflected in optimal energy usage and a longer network lifespan, as a greater number of nodes remain alive while accommodating the mobile sink's movement across inner and outer zones

Keyword: Mobile Wireless Sensor Networks, Mobile Sink, Data Aggregation, Mobile Environment, Network Dynamics

Introduction

Wireless Sensor Networks (WSN) utilizes low-powered devices called sensors that may be deployed across the coverage area to collect the field data. These sensors can be used for various applications as shown in Figure 1.

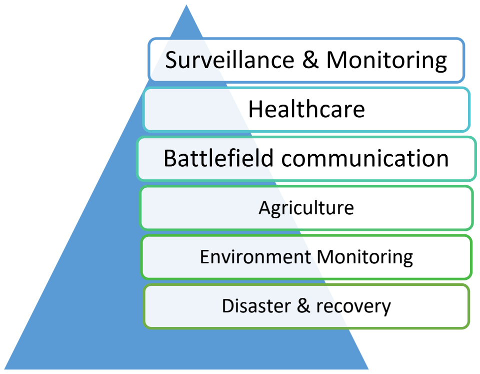

Figure: 1 WSN applications

In the mobile environment, the following are the different issues and challenges for WSN:

- **Energy efficiency:** Sensors are low-powered devices and network operations under the constraints of mobility may consume excessive resources and thus may reduce the overall network life-span.
- **Scalability:** Mobile sensors may move anywhere in the coverage area and thus may require long-range radio transmission support for transmission.
- **Reliable communication:** Mobile sensors may exchange data at high speed thus causing frequent packet drop, signal interference, congestion over the network and finally, it reduces the transmission quality.
- **Security:** Due to a lack of centralized security provision, intruders can also introduce malicious devices to intercept the transmission.

- **Routing:** Due to node mobility, routing paths are frequently updated and it may cause extra control overhead and excessive routing load thus reducing the performance of the routing protocol.
- **Data Aggregation:** This is another major challenge in a mobile environment as nodes can move anywhere in the network without completing the data handover data process [1-5].

As per the traditional approach, a cluster head (CH) is elected dynamically and it is responsible for data collection and aggregation from field sensors. In the case of mobile sensors, sensors may be dynamically connected to the current CH for data exchange thus increasing the control overhead for CH. This issue can be fixed using mobile sink-based aggregation that collects and aggregates the data from CH and forwards it to the base station. This method is highly efficient as compared to traditional CH-based aggregation and the following are its advantages as discussed below:

- Dynamically data collection and aggregation from nodes
- Movement across the entire coverage area
- Reliable transmission
- Control overhead management[6-10]

As the mobile sink moves across the entire network under the restrictions of coverage area, it has the following constraints as mentioned below:

- **Estimation of the next movement path for the mobile sink:** It is uncertain to determine the movement path of the mobile sink and if there are multiple mobile sinks then it is quite complex to estimate the unique traversal path for each mobile sink as each mobile sink must contain a unique list of sensors for data collection. Mobile sensors may witch their location dynamically, so becomes more complex to determine their current location w.r.t. current traversal path [11-16].
- **Movement management across the entire network:** mobile sinks may move anywhere inside the network but there is no standard approach to control their movement as well if there is no data to aggregate or the intermediate sensor is dead, still mobile sink will traverse the entire path to complete aggregation process thus may cause unnecessary resource consumption[17-21].
- **Frequent location update of the different sensors:** Mobile sensors or CH may update their location and there is a need to update the traversal path accordingly, however, it is quite complex to update it frequently and mobile sink may visit inconsistent sensor/CH location unnecessarily. In another case, if the mobile sink does not approach CH for data aggregation, in this scenario, sensors will transmit the data to CH unnecessarily and the base station will never get any update [22-30].

2. Literature Survey

Data aggregation is a critical operation over WSN and it may consume excessive network resources. Different researchers have introduced various solutions to resolve this issue using different techniques and the following section highlights the recently developed solutions for optimal data aggregation under resource-constrained WSN. R. Chitra et al. [31] used a clustered architecture-based compressive sensing method to aggregate the data over mobile sensor networks. Analysis shows that its performance may vary w.r.t. network architecture/size and the type of mobile sink. As compared to traditional compressive sensing, it outperforms in terms of extended network lifetime. T. Gupta [32] presented a data gathering and aggregation scheme that uses mobile sinks to build the data collection paths w.r.t. current routing links. Analysis shows that it is more efficient as compared to traditional data-gathering schemes in terms of optimal energy consumption and throughput and delay etc. P. Majumder et al. [33] proposed a spatial correlation-based data aggregation method for WSN. It collects the data from different geographical locations using low-intensity transmission thus results reduces the overall energy consumption of sensors. Analysis shows that it consumes optimal network resources as compared to traditional radio transmission. S. Venkatasubramanian et al. [34] presented an optimal cluster head selection scheme using butterfly optimization. It uses multiple mobile sinks to collect the data from sensors and perform aggregation. Analysis shows that it preserves and extends the network life as compared to the single mobile sink-based aggregation method. P. K. V. P. Shanmugapriya et al. [35] used static and mobile cluster-based data aggregation. Routing paths are periodically updated w.r.t. current location of the cluster head thus reducing the routing overhead and intermediate sensors can directly forward the data to the current cluster head. Analysis shows that it outperforms in terms of optimal energy consumption as compared to static networks. A. Sharma et al. [36] investigated the issues related to data aggregation over remote sensor networks and found that there are different constraints (i.e. redundancy, distance, transmission range etc.) that can reduce the accuracy of data aggregation. The findings of this study can be utilized to develop the optimal data aggregation solution. A. Shinde et al. [37] developed a solution for data aggregation over WSN. It uses a genetic algorithm for the optimal cluster head distribution/selection using cost estimation methods as well as it also selects the member nodes w.r.t. each cluster head. Analysis shows that it is an energy-efficient data aggregation solution as compared to existing cluster head selection methods. T. Batool et al. [38] proposed a multilevel data aggregation scheme. First of all, data is collected at the cluster and after aggregation, it is further transmitted to a centralized gateway that also performs the aggregation over incoming data and finally, it is forwarded to the base station. Analysis shows that it consumes less energy as compared to existing data aggregation schemes. A. Bomnale et al. [39] investigated the issues related to the efficient utilization of resources (as cluster head and sink node both consume higher resources as compared to other nodes) and developed a scheme that builds the shortest paths between sink node and field sensors and finally, a data aggregator is selected to process the data. Analysis shows that dynamic selection of the nodes for data aggregation consumes fewer resources thus resulting in extended network life-span. R. Amutha et al. [40] developed a nature-inspired algorithm to perform aggregation over WSN. It also uses a machine learning classifier to enhance the accuracy of aggregation. Analysis shows that it outperforms in terms of higher accuracy of aggregation with optimal resource consumption as compared to existing algorithms. S. Goel et al. [41] presented an optimal CH selection problem in WSNs using a hybrid optimization technique. The proposed WIFN algorithm performed better than LEACH, SEP-E, ERP, DRESEP and other methods. A mobile sink-based aggregation technique was created by S. Boyineni et al. [42]. It uses random forests to construct routing patterns and takes into account barriers to the mobile sink's mobility, which is employed for dynamic data aggregation. In comparison to current methods, analysis reveals that it conducts effective data aggregation with optimal energy consumption and lowers transmission delay. An energy-constrained data aggregation for WSN was proposed by J. G. Hannah et al. [43]. To gather the data from cluster heads for aggregation, it creates a tree. According to the results, it increases the network's lifespan by using optimal energy resources and minimizing frequent energy loss. S. Visishta et al. [44] introduced a data aggregation scheme that selects the cluster using different parameters i.e. bandwidth and residual energy. As compared to existing schemes (i.e. LEACH/ LEACH-C/ LEACH-F), it supports efficient data aggregation over a heterogeneous network environment. S. Gavel et al. [45] presented a data aggregation for WSN. First of all, at the node level, data is collected from the field and using data fusion, it filters out the redundant data. Experiments show that it is a solution as compared to data aggregation schemes. B. N. Sudheer et al. [46] investigated the different techniques to aggregate the data over WSN and these are cluster-based, mobile sink-based and compression sensing-based schemes. The study also found that there is a need to improve these schemes to enhance the data aggregation efficiency and accuracy under the constraints of limited resources. B. Bhasker et al. [47] presented a clustered-based data aggregation method for WSN. It selects the clusters in random order to perform the aggregation. As compared to other aggregation methods i.e. LEACH and LEACH-C, it delivers higher network lifetime, optimal packet delivery ratio, and energy consumption with minimal packet drop and delay. T.S. Praba et al. [48] integrated reinforcement learning to determine the traversal route for the mobile sinks that are used to collect the data from cluster heads. Experiments show that optimal traversal of mobile sinks reduces the extra control overhead as well as it also improves the efficiency of the data aggregation as compared to existing approaches. W. K. Yun et al. [49] developed a Q-learning approach to perform the data aggregation over WSN. It uses a reinforcement algorithm to select the optimal path to collect and aggregate the data over the network. Simulation analysis shows that it utilizes optimal resources for data aggregation as compared to existing energy-aware data aggregation schemes. M. R. Choudhar et al. [50] explored the different approaches to aggregate the data over WSN. It provided an overview of network-based, hierarchical and structure-free based aggregation etc. Study shows that each approach has its merits and limitations and these approaches can be used as per the application requirements. G. A. Macriga et al. [51] optimized the clustering and routing methods to enhance the data aggregation efficiency over WSN. It forms a greedy tree under the constraints of residual energy and the shortest path to forward the data towards the cluster head that proems data aggregation. Analysis shows its performance in terms of minimal routing overhead and optimal energy consumption as compared to existing schemes. An airborne data aggregation approach was introduced by A. S. Mohammed et al. [52]. For data transmission and aggregation, it dynamically changes the node's status from idle to active. After completing these tasks, the node returns to idle to conserve network resources. It is an energy-efficient data aggregation technique that can be used to gather data at remote locations where human intervention is impractical, according to experiments.

R.N. Kumar et al. [53] proposed an optimal data aggregation scheme for WSN. It uses K-means clustering to build the clusters for data aggregation then it selects optimal routing paths for data forwarding to the clusters. Analysis shows that it supports reliable transmission with optimal energy consumption, higher throughput with optimal delay etc. as compared to existing schemes. S. Zhai et al. [54] developed a data aggregation scheme that uses multiple nodes for data collection and aggregation. Simulation-based analysis shows that it reduces redundant data and optimizes energy consumption as compared to existing schemes. I.K. Abbood et al. [55]

investigated the various issues associated with data collection, aggregation and data reduction for WSN. The study found that common issues are optimal data processing under the constraints of limited resources, redundant data filtering, bandwidth utilization etc. All these are still open issues and the current study can be further utilized to improve the network performance. T.C. Dao et al. [56] introduced a heuristic-based data aggregation approach for WSN. It estimates the volume of the current data stream and filters out the redundant data during aggregation. Results show that it consumes less energy as compared to existing data aggregation schemes. D. Fotue et al. [57] proposed an efficient data aggregation for WSN. It forms a data processing metric and selects the optimal nodes only those that have higher connectivity with cluster head and finally, a tree is built to aggregate the data. Simulation results show that it reduces power consumption and supports optimal data aggregation with minimal delay. S. Itaya et al. [58] developed a prototype to aggregate the data over a distributed network. It builds a time-space computational metric to process the incoming data. Analysis shows that it is a more efficient scheme as compared to existing methods in terms of energy consumption and network throughput. An energy-efficient data aggregation strategy was presented by V. Prakash et al. [59] that use a meta-heuristic approach to build the clusters under the various constraints (current energy status, intermediate distance, and node density) to aggregate the data. According to simulation results, it performs better than current systems in terms of optimal energy consumption and longer network lifespan.

A blockchain-based data aggregation approach for WSN was created by K. Soundarapandian et al. [60]. During data aggregation, it employs techniques for data compression and decompression. According to simulation-based results, it employs a lightweight compression, which lowers the total computational cost when compared to other approaches.

Table 1: Recently developed solution of mobile wireless sensor networks

Reference	Author(s)	Objective	Method	Limitation	Conclusion
[31]	R. Chitra et al.	clustered architecture -based data aggregation	compressive sensing	Dependency on mobile sinks	Suitable for large-scale WSN
[32]	T. Gupta	data gathering and aggregation	mobile sinks	Aggregation accuracy may vary due to Wireless links	optimal energy consumption
[33]	P. Majumder et al.	Data aggregation over Heterogeneous networks	Location-aware data forwarding	Data compatibility	optimal network resource consumption
[34]	S. Venkatasubramanian et al.	optimal cluster head selection	multiple mobile sinks	Data synchronization between mobile sinks	extend the network life
[35]	P. K. V. P. Shanmugapriya et al.	Cluster-based data aggregation	static and mobile sinks	Location dependency	Minimal energy consumption
[36]	A. Sharma et al.	Review of data aggregation issues	Review of different constraints related to data aggregation	The scope of the Study considers data aggregation issues only	Highlights the barriers for aggregation over WSN
[37]	A. Shinde et al.	Cluster-based aggregation	Genetic algorithm	Complexity	Energy-efficient data aggregation

[38]	T. Batool et al.	Optimal data aggregation	multilevel data collection	Accuracy	Optimal energy consumption
[39]	A. Bomnale et al.	Efficient utilization of resources	Selection of shortest links between sink and field sensors	Stability of wireless links	Extended network life-span
[40]	R. Amutha et al.	Optimizatio n of resource consumptio n for data aggregation	nature inspired algorithm	Complexity	higher aggregation accuracy
[42]	S. Boyineni et al.	Data aggregation	Mobile-based data collection	Sink dynamics	Minimal transmission delay for aggregated data
[43]	J. G. Hannah et al.	energy constrained data aggregation	Tree-based data collection	Excessive Tree traversal	Minimal energy drain during aggregation
[44]	S. Visishta et al.	data aggregation over heterogeneo us environment	Cluster-based aggregation	Used traditional aggregation algorithms only	Efficient data aggregation
[45]	S. Gavel et al. [45]	data aggregation for WSN	redundant data filtering using the data fusion method	Accuracy	energy efficiency
[46]	B. N. Sudheer et al.	Dynamic data aggregation	compression sensing	Mobile sinks	Efficient utilization of limited resources
[47]	B. Bhasker et al.	clustered-based data aggregation	random ordering of clusters	Considered only traditional methods (LEACH/LE ACH-C)	higher network lifetime
[48]	T.S. Praba et al.	Optimizatio n of traversal route for mobile sinks	reinforcement learning	Route estimation accuracy	Optimal control overhead
[49]	W. K. Yun et al.	Selection of optimal paths for aggregation	Q-learning approach	Variation inaccuracy	Energy-aware data aggregation
[50]	M. R. Choudhar et al.	Overview of aggregation methods	Analysis	Did not include the latest trends in aggregation	Highlights the merits & demerits of different aggregation schemes

[51]	G. A. Macriga et al.	Clustering based aggregation	greedy tree	Tree manageme nt	optimal energy consumption
[52]	A. S. Mohammed et al.	aerial data aggregation	Sate switching	Operational cost	Support for remote data collection
[53]	R.N. Kumar et al.	Efficient data aggregation	K-means clustering	Optimal selection of routing paths	reliable transmission
[54]	S. Zhai et al. [54]	Filtering of redundant data	multiple nodes-based aggregation	Computatio nal cost	Minimal energy consumption
[55]	I.K. Abbood et al.	Duplicate data reduction	Survey	Theoretical analysis only	Optimal resource utilization
[56]	T.C. Dao et al.	Duplicate data filtering	Heuristic approach	Computatio nal cost	Efficient energy consumption
[57]	D. Fotue et al.	Efficient data aggregation	data processing metric	Control overhead	power consumption
[58]	S. Itaya et al.	Data aggregation	time-space computationa l metric	prototype only	Extended network throughput
[59]	V. Prakash et al.	Cluster-based data collection	meta-heuristic approach	Control overhead	Enhanced network life-span
[60]	K. Soundarapan dian et al.	data aggregation	Compression/ decompressio n	Complexity	Optimal data processing

3. Research Gaps

As per the above discussion and findings mentioned in Table1, recently developed solution of mobile wireless sensor networks, it can be observed that most researchers focused on the common concept i.e. efficient data aggregation w.r.t. resources i.e. energy consumption, residual energy, bandwidth utilization, control overhead and network throughput etc. Researchers highlighted the usage of advanced-level methods i.e. compressive sensing, heuristic and Genetic algorithms mobile sink-based aggregation and cluster head-based data aggregation are the most common methods for static sensor networks however, only a few researchers used mobile sinks for aggregation and energy efficiency and optimal data aggregation both are still open issues and there is need to optimize the resource consumption to improve the network lifespan.

4. Proposed Scheme

In this paper, a mobile sink-based data aggregation method is introduced that collects the traversal path information from the current cluster head and traverses the path to collect and aggregate the data from sensors. The following section describes its various operations as shown in Figure 2.

First of all, subdivide the coverage area/4 into local zones Lz

Deploy mbs mobile sinks w.r.t. each Lz

$$\sum mbs = \sum Lzi$$

Sensor Side

Phase i: in this phase, a data sense cycle is defined and sense data is added to the sensor's buffer, if the buffer is full then for data collection, it broadcasts its id to the current CH with the following parameters are essential to define the movement of mbs and at least 1 sensor must be in the field to initiate the request for the movement.

(i) Msg (id, distance, timestamp, buffer length)

Phase ii: this phase defines the transmission cycle. First of all, the sensor senses the data from the field and saves it into its buffer and if the buffer is full then it generates a request to the current CH for data collection it waits for the acceptance from CH and switches its state to idle state.

Phase iii: In this phase, if data collection acceptance is received by the sensor through CH, it changes its state to active and sends all data to mbs and clears its buffer and starts the data sensing again.

Cluster Head Side

Phase I: In this phase, CH estimates the current of the traversal path for ∑mbs. First of all, it collects the incoming request using the sensor's ID and minimum distance from CH and adds this information to the traversal path and after processing all requests, finally, it performs ascending sorting over the traversal path and initiates the request to mbs for data collection and aggregation process. If mbs is idle, then the incoming request is accepted and the current CH shares the current traversal path with mbs and finally, traversal is determined by the following phase.

Phase ii: In this phase, after getting the clearance, the current traversal path is discarded and phase I is repeated, if required.

Mobile sink side

Prerequisites for the movement of mbs

Following are the constraints for the mbs for inner zone movement:

(i) Define $th = \sum$ Initiale/10 and th must be greater than e that is required to move the mbs up to distance d

(ii) The mbs is allowed to move only if its current residual energy is greater than the predefined energy threshold th.

(iii) $\sum Td = \sum d\ X \sum n$, where d is the intermediate distance to travel to nth location at the speed of sp and if energy e is required to move the mbs up to d distance than for the traversal of $\sum Td$ path, total $\sum Te = \sum e \times \sum Td$ is required. If $\sum Te < \sum$ *Initial e/2*, reduce the set sp=*sp/2* and if it is less than threshold th, then stop movement.

(iv) To process the data of each sensor in the traversal path, if e is required to process the p packet then total energy $\sum Te = \sum e\ X \sum p$ is required to process the current buffer of a sensor.

Phase III: In this phase, mbs movement is defined as per following:

(a) Inner zone movement: in this phase, first of all, the traversal path is initialized and it is treated as mbs movement route mvr and it is restricted to forward direction only. As per the mvr, it collects the data from each sensor and after performing aggregation, it removes the sensor's ID from the mvr, to avoid the revisit. After the entire path traversal, mvr is discarded and mbs becomes idle. The above steps may be repeated if required.

(b) Outer zone movement: in this phase, if the mbs are dead or unavailable in any other zone, then the current CH on that zone broadcasts a global data collection request and if any mbs accept its request, CH prepares a global traversal path and also adds its location and shares it with mbs. At the same time, if mbs receives multiple requests, then it performs sorting over the global traversal path and it defines its movement w.r.t. current mvr in other zones and so on. After path traversal, it discards the mvr for the specific zone. These steps may be repeated if required.

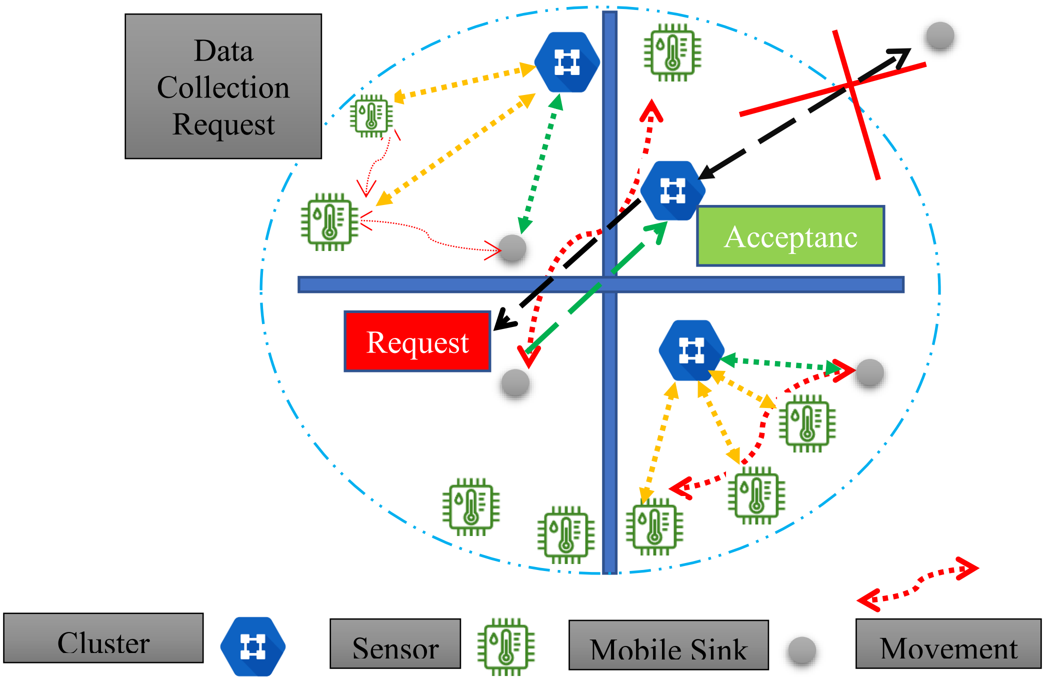

Figure 2: Movement of mobile sinks in different zones

5 Experimental Setup and Results

For analysis, network simulator version 3 (NS-3) was used over the Linux platform with sensor density 100-300 only, RX/TX 10, coverage area 1500m x 1500m, routing protocols: LEACH and TEEN, initial energy 7J, mobility model: RandomWayPoint, maximum speed 20 meter/second, packet size 1024 bytes, Propagation Model: Friis Propagation Loss Model and simulation time 10 seconds.

5.1 Performance analysis of LEACH and MBS-LEACH

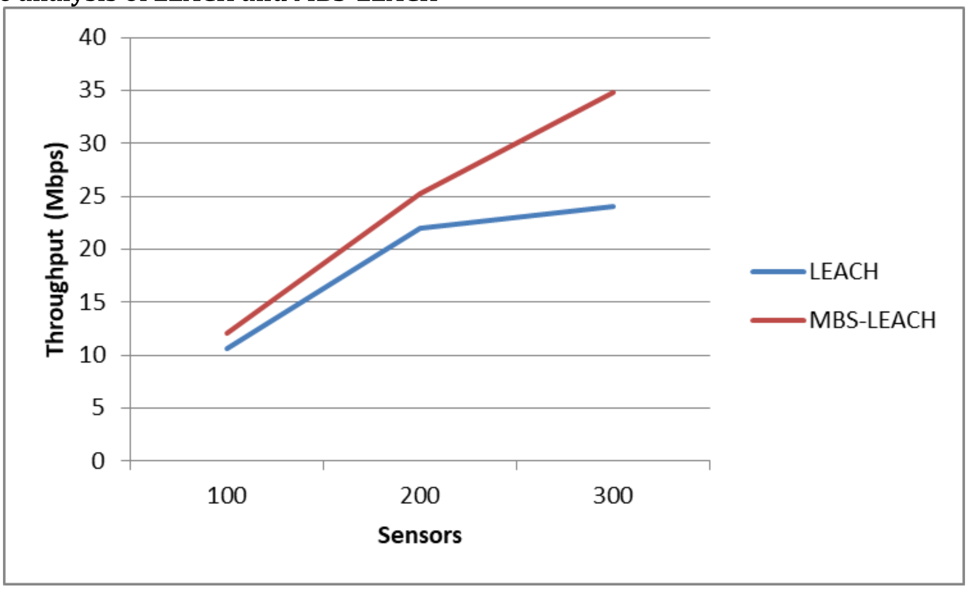

Figure 3: Throughput comparison

Figure 3 shows the Throughput of two different scenarios i.e. LEACH and MBS-LEACH. In the case of LEACH, using 100 sensors, it is 10.58797Mbps for LEACH and 12.10054Mbps for MBS-LEACH, with 200 sensors, it is 22.04126Mbps for LEACH and 25.19001Mbps for MBS-LEACH, with 300 sensors, 24.09023Mbps for LEACH and 34.83095Mbps for MBS-LEACH. It can be seen that in both cases, it is increasing w.r.t. variations in sensor's density however, it is quite less for LEACH as compared to MBS-LEACH and with the highest sensor density, it reaches up to its peak level and on other hand, it is slightly declined for LEACH.

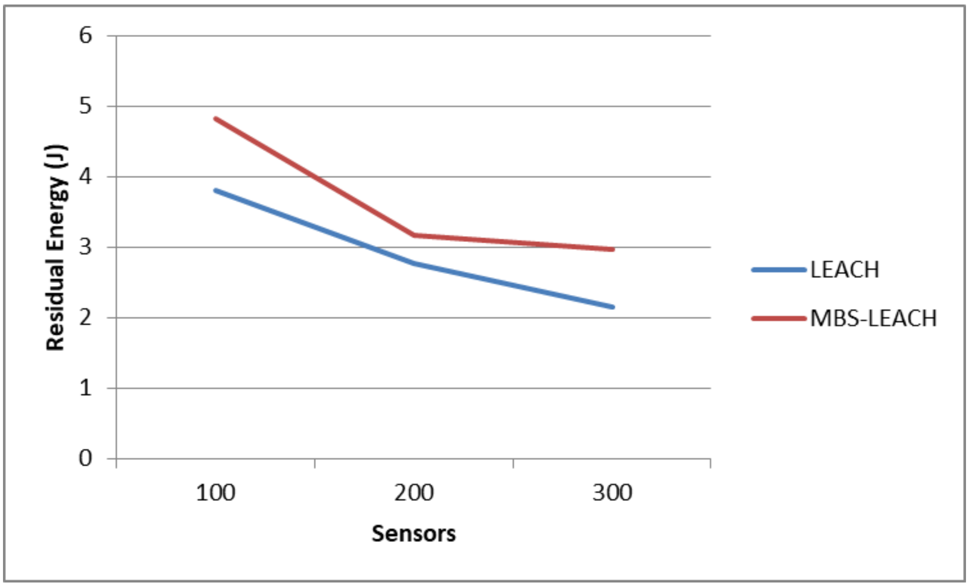

Figure 4: Residual energy comparison

The residual energy of two distinct scenarios—LEACH and MBS-LEACH—is displayed in Figure 4. With 100 sensors, it is 3.81059J for LEACH and 4.81393J for MBS-LEACH; with 200 sensors, it is 2.7642J for LEACH and 3.17261J for MBS-LEACH; with 300 sensors, it is 2.15934J for LEACH and 2.97354J for MBS-LEACH. It is evident that it is declining in both scenarios with respect to variations in sensor density, but it is much lower for LEACH than for MBS-LEACH, and it declined to its lowest level for both scenarios with the highest sensor density. Nevertheless, MBS-LEACH maintained its acceptance level in contrast to LEACH, which was unable to maintain the necessary energy level under the constraints of a scalable network.

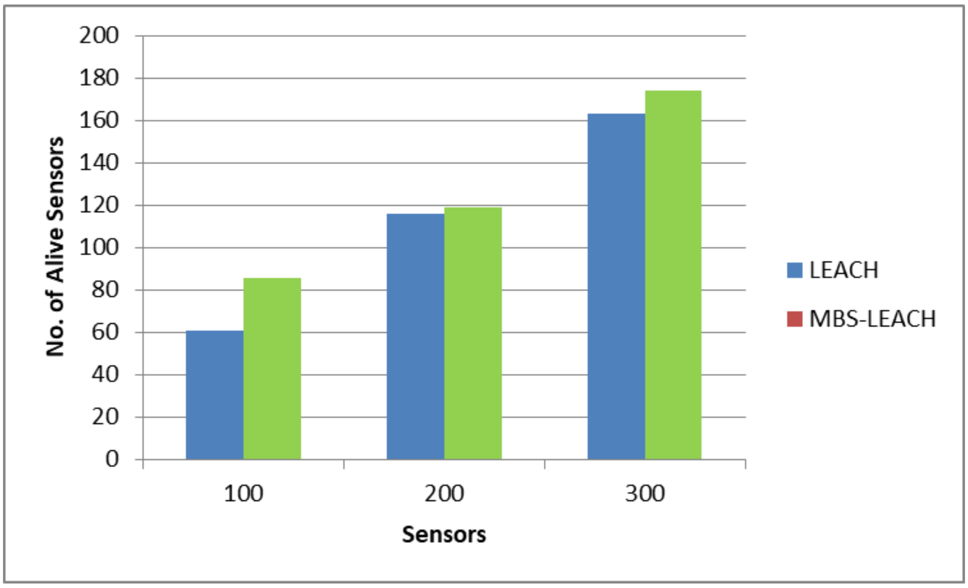

Figure 5: Number of Alive sensors

The number of active sensors in two distinct scenarios—LEACH and MBS-LEACH—is displayed in Figure 5. Regarding LEACH, there are 61 active sensors out of 100 for LEACH and 86 for MBS-LEACH, with 200 sensors; these are 116 for LEACH and 119 for MBS-LEACH, with 300 sensors, 163 for LEACH and 174 for MBS-LEACH. The number of alive sensors varied with sensor density in both scenarios, and as sensor density increased to its peak value, fewer alive sensors were present. Nevertheless, MBS-LEACH maintained a higher number of alive sensors than LEACH under the constraints of sensor density.

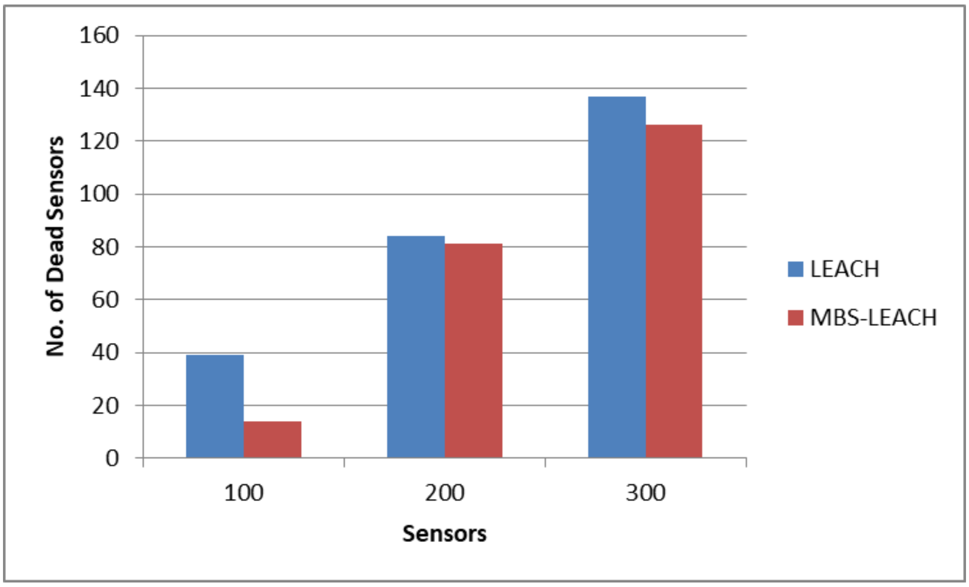

Figure 6: Number of Dead sensors

The number of dead sensors—those that were unable to survive throughout simulation—for the two distinct scenarios—LEACH and MBS-LEACH—is displayed in Figure 6. In the instance of LEACH, there are 39 dead sensors out of 100 for LEACH and 14 for MBS-LEACH; 84 dead sensors out of 200 for LEACH and 81 for MBS-LEACH; and 137 dead sensors out of 300 for LEACH and 126 for MBS-LEACH. It is evident that the number of dead sensors varies with sensor density in both scenarios, with LEACH having more dead sensors than MBS-LEACH under sensor density limits.

5.2 Performance analysis of TEEN and MBS-TEEN

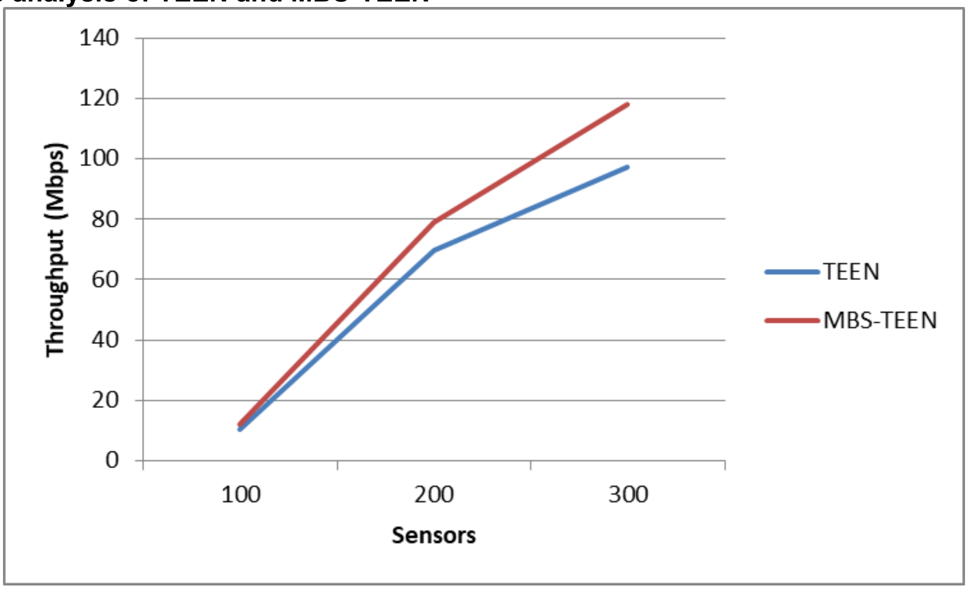

Figure 7: Throughput comparison

Figure 7 shows the Throughput of two different scenarios i.e. TEEN and MBS- TEEN. In case of TEEN, using 100 sensors, it is 10.48799Mbps for TEEN and 11.98627Mbps for MBS- TEEN, with 200 sensors, it is 69.59604 Mbps for TEEN and 79.11088Mbps for MBS- TEEN, with 300 sensors, 97.24701Mbps for TEEN and 117.90602Mbps for MBS-TEEN. It can be identified that in both cases, it is increasing w.r.t. variations in sensor's density however, it is quite less for TEEN as compared to MBS- TEEN and with the highest sensor density, it reaches up to its peak level and on other hand, it is slightly declined for TEEN.

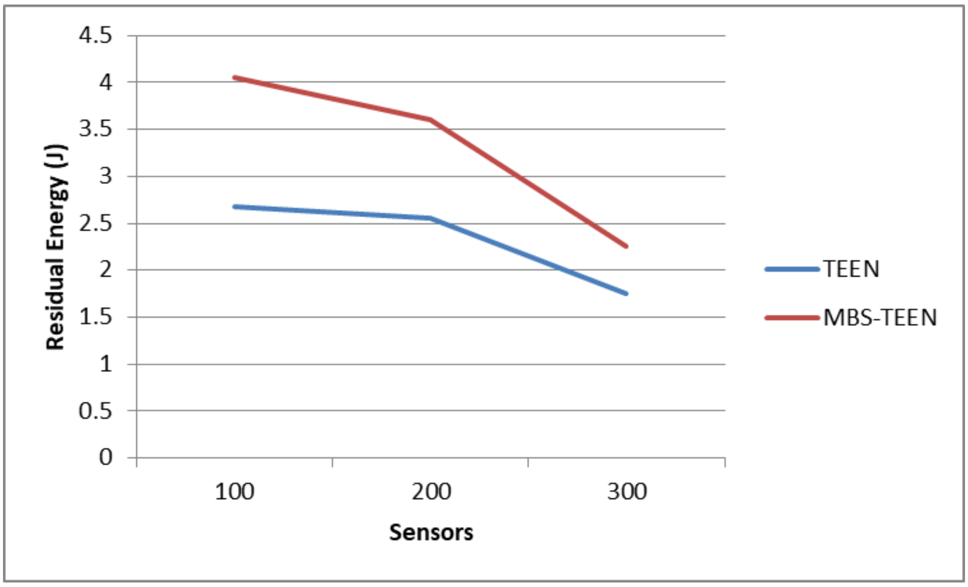

Figure 8: Residual energy comparison

The residual energy of two distinct scenarios—TEEN and MBS-TEEN—is displayed in Figure 8. With 100 sensors, it is 2.67299J for TEEN and 4.04875J for MBS-TEEN; with 200 sensors, it is 2.55002J for TEEN and 3.59967J for MBS-TEEN; and with 300 sensors, it is 1.75471J for TEEN and 2.24889J for MBS-TEEN. It is evident that it is decreasing in both scenarios with respect to variations in sensor density, but it is much less for TEEN than for MBS-TEEN. With the highest sensor density, it declined to its lowest level for both scenarios, but MBS-TEEN maintained its acceptance level in contrast to TEEN, which was unable to maintain the necessary energy level due to the density of sensor constraints.

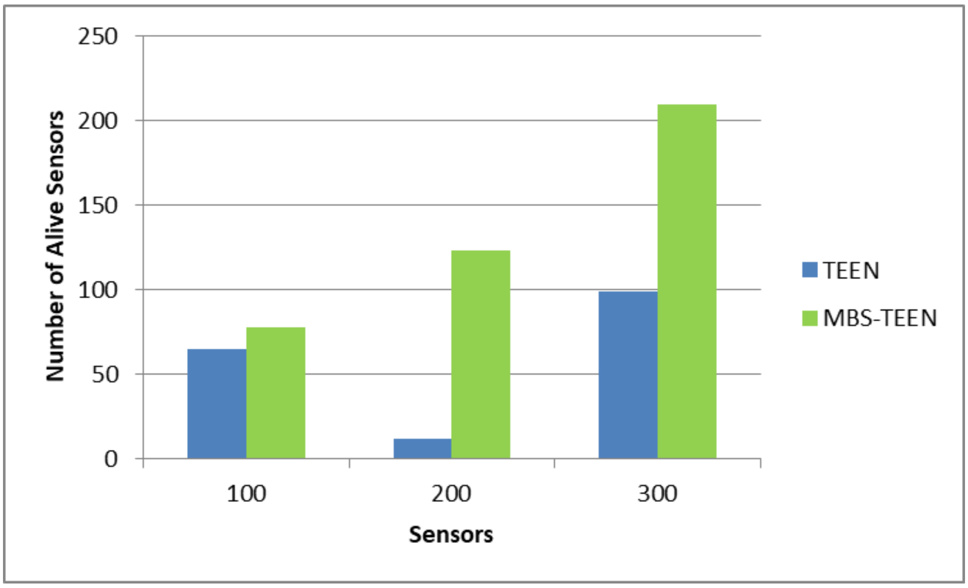

Figure 9: Number of Alive sensors

The number of active sensors in two distinct scenarios—TEEN and MBS-TEEN—is displayed in Figure 9. Out of 100 sensors, there are 65 for TEEN and 78 for MBS-TEEN; with 200 sensors, there are 12 for TEEN and 123 for MBS-TEEN; and with 300 sensors, there are 99 for TEEN and 209 for MBS-TEEN. It is evident that in both scenarios, the number of alive sensors fluctuated with sensor density and decreased as sensor density rose to its maximum value. Nevertheless, MBS-TEEN was able to maintain a higher number of alive sensors than TEEN despite the limitations imposed by sensor density.

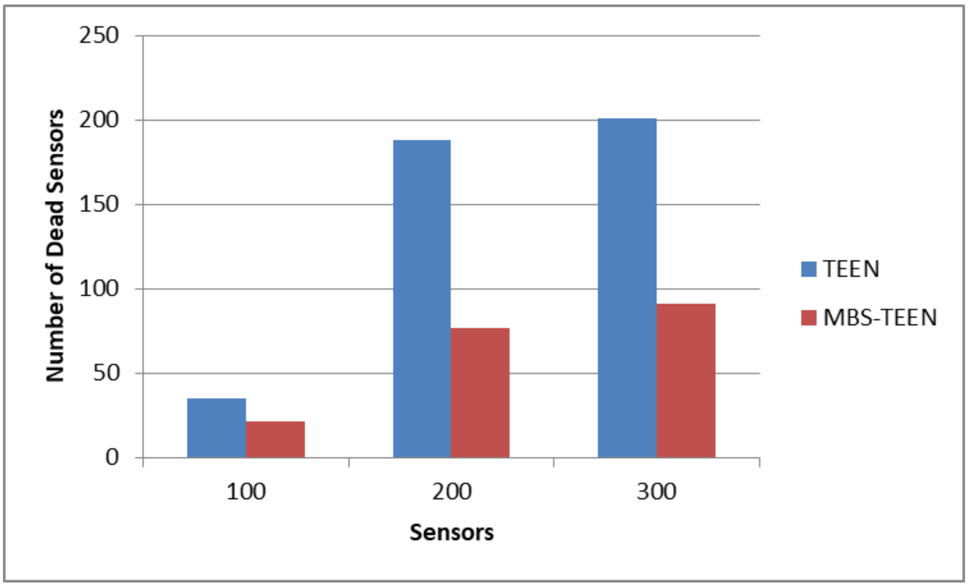

Figure 10: Number of Dead sensors

The number of dead sensors—those that were unable to survive during simulation—for the TEEN and MBS-TEEN scenarios is displayed in Figure 10. Out of 100 sensors, there are 35 for TEEN and 22 for MBS-TEEN; with 200 sensors, there are 188 for TEEN and 77 for MBS-TEEN; and with 300 sensors, there are 201 for TEEN and 91 for MBS-TEEN. It is evident that the number of dead sensors varies with sensor density in both scenarios, with TEEN having more dead sensors than MBS-TEEN under sensor density limits.

5.3 Movement of mobile sinks w.r.t. inner zone

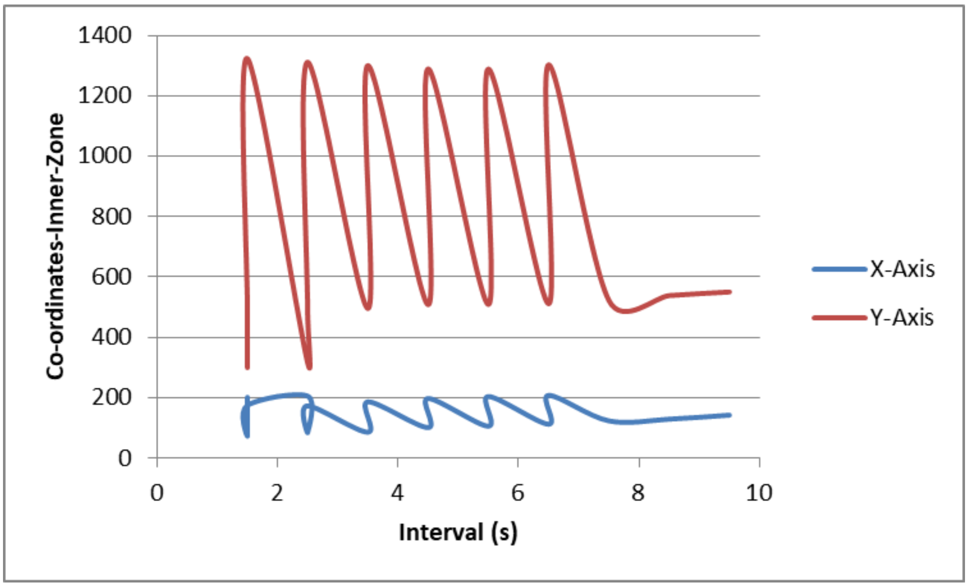

Figure 11: Movement of mobile sinks-100 sensors

Figure 11 shows the inner zone movement of mobile sinks with 100 sensors w.r.t. X-axis and Y-axis over the time interval 10 seconds. It can be observed that there are lots of variations in the X-axis as compared to the Y-axis.

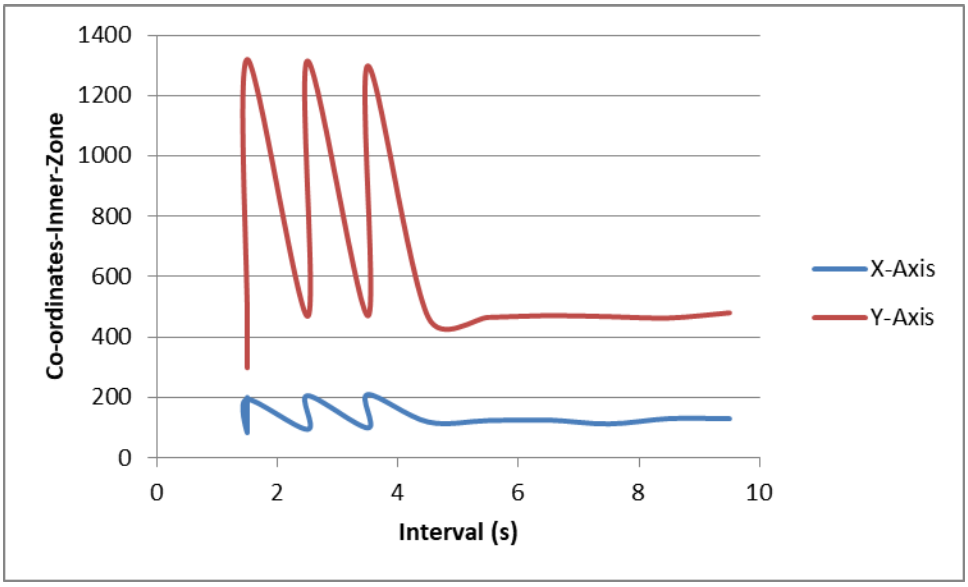

Figure 12: Movement of mobile sinks-200 sensors

Figure 12 shows the inner zone movement of mobile sinks with 200 sensors w.r.t. X-axis and Y-axis over the time interval of 10 seconds. It can be observed that there are similar variations in the X-axis as compared to Y-axis and over the interval, it is approx. Constant.

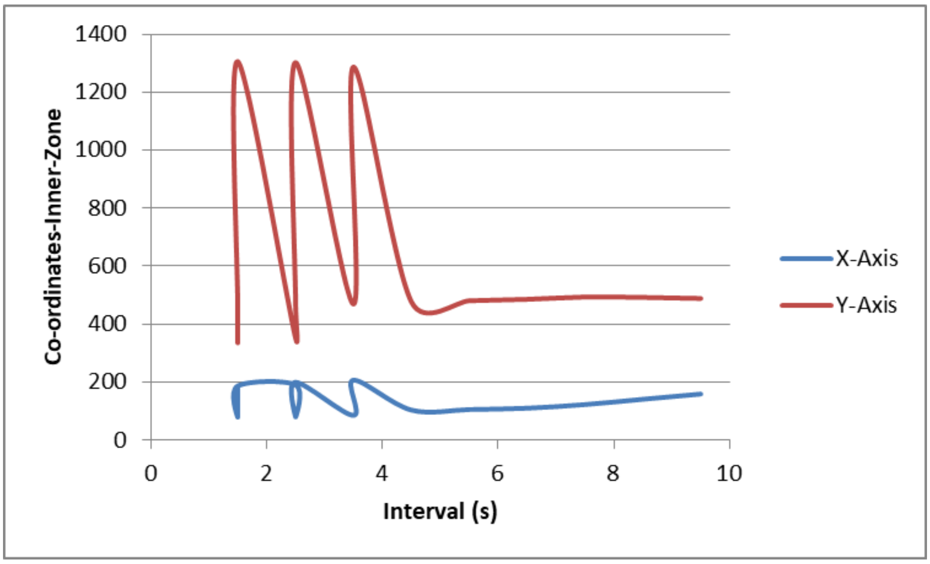

Figure 13: Movement of mobile sinks-300 sensors

Figure 13 shows the inner zone movement of mobile sinks with 300 sensors w.r.t. X-axis and Y-axis over the time interval of 10 seconds. It can be observed that there are little bit variations in the X-axis as compared to the Y-axis and over the interval, it is approx. Constant.

5. 4 Movement of Mobile sinks w.r.t. outer zone

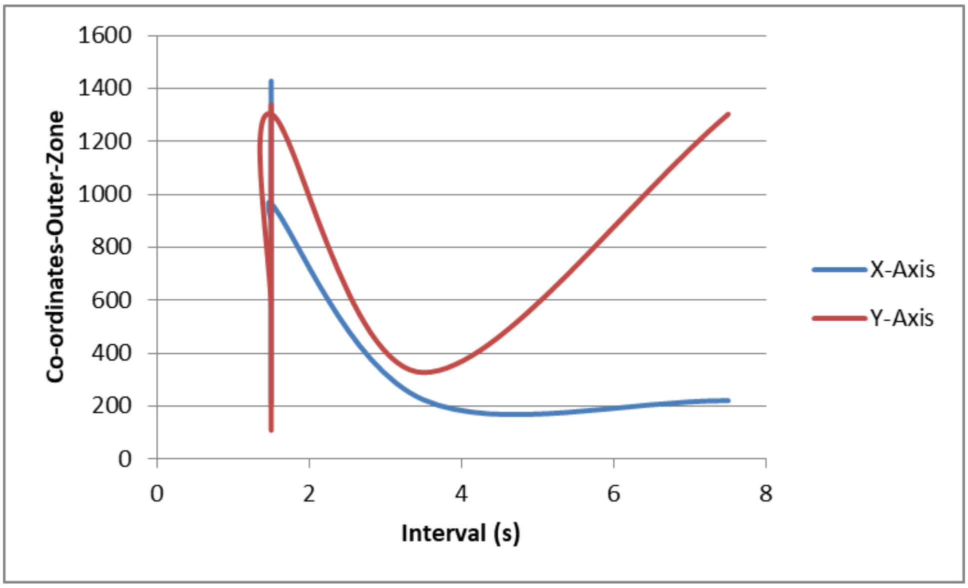

Figure 14: Movement of mobile sinks-100 sensors

Figure 14 shows the outer zone movement of mobile sinks with 100 sensors w.r.t. X-axis and Y-axis over the time interval of 8 seconds. It can be observed that in starting of the interval (up to 2 seconds) there is no movement across the X-axis where whereas there is vertical movement at the Y-axis.

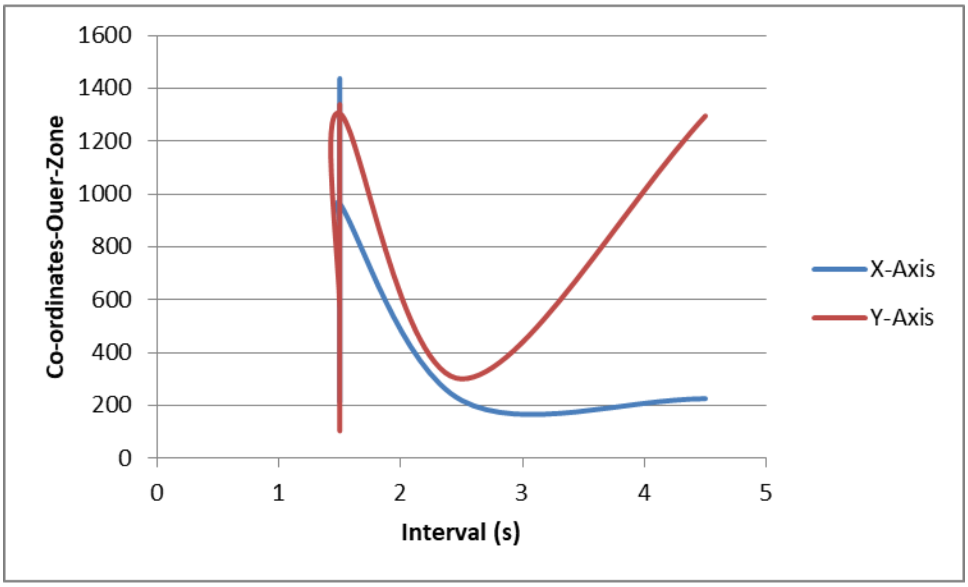

Figure 15 Movement of mobile sinks-200 sensors

Figure 15 shows the outer zone movement of mobile sinks with 200 sensors w.r.t. X-axis and Y-axis over the time interval of 5 seconds. It can be observed that at the start of the interval (up to 1.5 seconds) there is no movement across the X-axis whereas there are vertical movements at the Y-axis till the end of the interval.

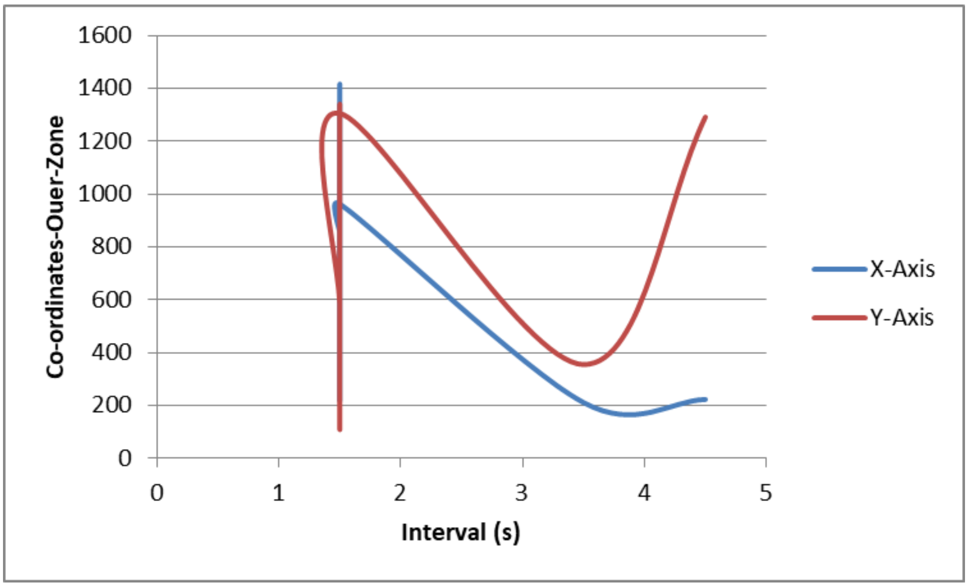

Figure 16: Movement of mobile sinks-300 sensors

Figure 16 shows the outer zone movement of mobile sinks with 300 sensors w.r.t. X-axis and Y-axis over the time interval of 5 seconds. It can be observed that there are quite less movements across the X-axis and later on, there are few movements at the X/Y-axes till the end of the interval.

Figure 17 shows the Frequency of movement of mobile sinks in Inner and Outer Zones under the constraints of the sensor's density (100-300 sensors). It can be observed that inside the inner zone, in the case of 100 sensors, it is 17, in the case of 200 sensors, it is 13 and it is 14 for 300 sensors and in the case of the outer zone, it is constant (19) w.r.t. sensor density that means there are excessive movements in the outer zone as compared inner zone.

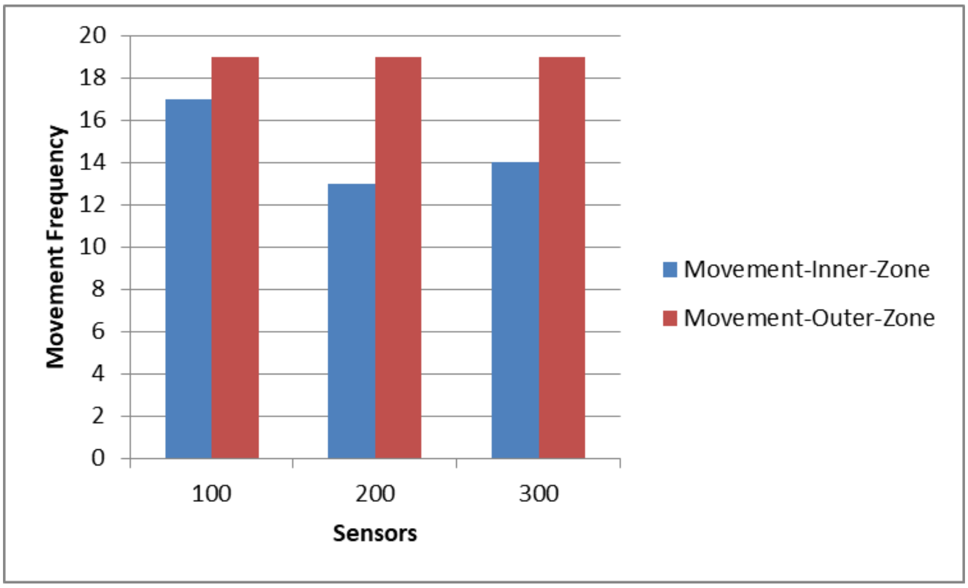

Figure 17: Movement Frequency of mobile sinks over Inner/Outer Zones

6. Results Discussion

When LEACH uses 100 sensors, throughput is at its lowest level. It then gradually increases when sensor density rises to 200 sensors, and at 300 sensors, it reaches its maximum level. According to the analysis, as the number of sensors increased throughout the network, it used more energy for network operations, which shortened the sensors' lifespan. In contrast, TEEN's throughput varied less than LEACH's, but it was still higher given the limitations of sensor density.

When MBS-LEACH uses 100 sensors, throughput is at its nominal level. As sensor density rises to 200 sensors, it is somewhat altered, and at 300 sensors, it hits its maximal level. According to the analysis, it was found that as the number of sensors in the network grew, so did the energy required for network operations, which shortened the sensors' lifespan. However, in the instance of MBS-TEEN, it grew within the limitations of the sensor density and produced a peak throughput value with the maximum sensor density.

Both LEACH and TEEN were unable to hold onto enough remaining energy. As the sensor's density reached its maximum value, it decreased to its lowest level. The lifespan of the sensors was shortened by excessive energy depletion, and there were more dead sensors utilizing TEEN and LEACH. Nevertheless, despite the limitations of sensor density, the suggested technique decreased its count to a manageable level, and MBS-LEACH and MBS-TEEN both maintained almost identical residual energy levels in comparison to conventional methods while retaining a greater number of active sensors.

Movement of the mobile sink is an independent operation and in the case of movements of mobile sinks w.r.t. inner and outer zones, it can be observed that there are different patterns of movements at the X-axis as compared to the Y-axis. In the case of inner zone movements, it can be analyzed that there is excessive movement at the X-axis as compared to the movements at the Y-axis. It can also be analyzed that there are few variations as the sensor's density varies from 100 to 300 sensors. In the case of 100 sensors, at both axes, there are lots of variations in movement; however, it gradually decreased for the Y-axis over the end of the interval for the sensor density 200 to 300.

In the case of outer zone movements, it can be observed that in starting of the simulation, it is quite less at the X-axis as compared to the movements over the Y-axis and later on, there are lots of variations in movements at both axes till the end of the interval. It can also be observed that the interval of movement in the outer zone is quite less (up to 5-8 seconds) as compared to the inner zone's movements. It also varies under the constraints of the sensor's density and there was steep up/down at the X-axis as compared to Y-axis.

As per the analysis of movement frequency, it can be analyzed that their movement frequency varied inside the inner zone and its minimum frequency is 13 for 200 sensors and maximum (17) for 100 sensors and it is at the medium level for 300 sensors whereas it is highest for the outer zone (19) having no variation w.r.t. sensor's density.

7. Conclusions

WSN gathers the data using various field sensors and there are different strategies to collect and aggregate the data. In this paper, a mobile sink-based data aggregation approach was introduced using LEACH and TEEN protocols, called MBS-LEACH and MBS-TEEN. Their performance was also compared with the existing LEACH/TEEN protocols under various constraints i.e. Throughput, residual energy, and sensor density that varied from 100 to 300 sensors. As per the simulation analysis and results, it can be observed as compared to MBS-TEEN and MBS-LEACH, the Throughput of LEACH and TEEN protocols is quite less and it was increased slightly as the sensor density varied from 100 to 300. In the case of energy consumption, LEACH/TEEN also consumed higher energy thus reducing the overall life-span of field sensors; however, the number of dead/alive sensors varied w.r.t. sensor's density. Due to the excessive energy consumption, LEACH and TEEN both could not retain a sufficient level of residual energy thus declining the overall life-span of the entire network and using MBS-LEACH and MBS-TEEN, higher Throughput was achieved at optimal energy consumption with a minimal number of dead sensors under the constraints of sensor's density variations. The scope of the current work explored the existing aggregation approaches and introduced the concept of mobile sinks with their controlled movements under the constraints of inner/outer zones using two protocols (i.e. LEACH and TEEN protocol) only. In the future, the proposed scheme will be extended to support the different networks (i.e. Internet of Things, Mobile Ad Hoc Networks and Vehicular Ad Hoc networks) to manage the quality of transmission under the constraints of high mobile environments.

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