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Efficient Clustering With Advanced Particle Swarm Algorithm

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Abstract: **Wireless sensor networks have principal characteristic of having restricted energy and with limitation that energy of the nodes cannot be replenished. To increase the lifetime in this scenario WSN route for data transmission is opted such that utilization of energy along the selected route is negligible. For this energy efficient network, dandy infrastructure is needed because it impinges the network lifespan .Clustering is technique in which nodes are grouped into disjoints and non –overlapping sets. In this technique data is collected at the cluster head. In this paper Adaptive-PSO algorithm is proposed which forms energy aware clusters by minimizing the cost of locating the cluster head. The main concern is of the suitability of the swarms by adjusting the learning parameters of PSO. Particle Swarm Optimization converges quickly at the beginning stage of the search but during the course of time it becomes stable and may be trapped in local optima. In suggested network model swarms are given the intelligence of the spiders which makes them capable enough to avoid earlier convergence and also help them to escape from the local optima. Comparison analysis with traditional PSO shows that new algorithm considerably enhances the performance where multi dimensional functions are taken into consideration.**

***Index Terms*—PSO, APSO, Comparison between PSO and APSO**

I. INTRODUCTION

All wireless sensor networks supply new applications for setting watching, and military police investigation applications [1]. Recent developments in hardware shrinking combined with low-cost production and advances in wireless communications technologies have created gettable applications with huge numbers of sensors. In some [2] cases ground access to the realm of the objectives to be monitored is difficult or dangerous, so one resolution to place within the sensors is to deploy them from academic degree craft.

A wireless sensing element network [3] of the sort investigated here refers to a bunch of nodes, or sensors that unit of measurement coupled by wireless medium to perform the distributed sensing tasks. Connections between the nodes is additionally intentional practice such media as infrared devices or radios.

By human activity sensing, signal method, and communication functions, a sensing network gives a natural platform for stratified the field of study [4]. It allows information to be processed on completely different levels of abstraction, microscopic examination of specific targets, ranging from the elaborate, to the macroscopic browse on mixture behaviour of targets. Any events inside the setting square measure processed [5] on three levels: node level, the native neighbourhood level, and world level. In node level, data assortment and method happens in each individual node, requiring no communications aside from the transmission of results to some distant information sink. On native and world level [6], inter-node communication is required for collecting raw or pre-processed data from numerous nodes to 1 location for cooperative signal method like data fusion or beam-forming.

This Hardware category [7] includes the full diverge of activities related to the hardware platforms that comprise sensor networks. MEMS sensor [8] technology could be important side of this category. (MEMS) self-powered sensor and RF transmission platform for wireless sensor network (WSN) nodes which can operate at energy levels orders of magnitude lower than current equivalent systems. Using the micro generator as a power amplifier to drive passive kick-and-resonate transmitter architecture as an alternative to a standard power hungry transmitter, this platform eliminates the need for both secondary energy storage and power conditioning circuits. This enables a significant reduction in the size, weight, complexity and cost, and allows operation at much lower excitation frequencies. The prototype platform consists of a MEMS rolling-rod micro generator, the output voltage of which is used to kick a resonant loop antenna. The generator can be directly primed by a suitable voltage-output sensor. This is the first platform to achieve wireless sensor transmission powered only by a MEMS energy harvester.

Applications-At the applying layer [10] processes aim to form effective new capabilities for economical extraction, manipulation, transport and illustration data information of information of data derived from sensor data. In most applications [11], sensor networks have speckled purposeful components such as: detection and data assortment, signal method, data fusion, and notification.

Energy-efficiency means that the energy used up on forwarding packets from a Source (Sensor node) to a target (Base Station) should be less, since the energy required for sensor nodes is in general particularly restricted. With the help of Energy Efficient Clustering Algorithms, the energy can be conserved and utilized for an extended time period and the certain expiry of sensor nodes can also be prevented.

WSNs are deployed in an ad-hoc manner and have a large number of nodes. The nodes are in general naive of their positions. Therefore, dispersed clustering protocols that depend only on neighbourhood information are favoured for WSNs. Above and beyond, nodes in WSNs function on battery power with partial energy. Thus, the employed clustering technique must have small message overhead. Lastly, harsh environmental circumstances also result in unanticipated failure of nodes. Hence, periodic re-clustering is required in order to heal cut off regions and spread energy consumption across all nodes. Periodic re-clustering is also obligatory, as the parameters used for clustering (e.g., the remaining energy, node degree etc.) are dynamic.

A WSN classically consists of many small, low cost, low-power communication devices called sensor nodes. Each sensor node has partial on-board processing, limited storage and radio capacities. Due to the limited and non-rechargeable energy supply (e.g. battery), WSNs have severe necessities about power consumption. Therefore energy-efficient protocols are necessary to save energy and extend network lifetime.

We cluster sensors into groups, so that sensors communicate information only to cluster head and then the cluster heads communicate the aggregated information to the base station, which will save energy. Cluster-heads are accountable for organization among the nodes inside their clusters (intra-cluster coordination) and communication, with each other and/or with external observers on behalf of their clusters (inter-cluster communication).

II. ENERGY CONSUMPTION STATES

Energy is an assessment because WSNs are powered by batteries. This energy can be very expensive, difficult or even impossible to stock up. Consequently saving energy to exploit network lifetime is one of the serious tribulations in wireless ad hoc and sensor networks. Numerous solutions are proposed to improve the network lifetime. In WSNs, nodes disperse energy in processing and transmitting/receiving messages. In addition to this energy, there is a great amount of energy necessary in states that are unproductive from the application point of view, such as:

Idle listening: In view of the fact that a node does not know when it will obtain a message; it must lastingly listen to the medium and so it snippets in the idle state.

Overhearing: When a sender transmits one packet to next hop, because of the shared nature of wireless medium, all neighbours of the source obtain this packet even if it is proposed to only one of them. As a result the overhearing is the energy debauching, when the node is a one-hop neighbour of the sender.

Interference: Each node located between transmitter range and intervention range gets this packet but it cannot decode it.

Collision: In case of CSMA/CA medium access, when a crash occurs, the energy dissolute for the broadcast and for the reception of colliding frames is exhausted.

The energy controlled nature of wireless nodes needs the use of energy efficient technique to minimize the energy wasted in these useless states; such as to maximize network lifetime. In all cases, an energy consumption model is needed to conclude in favour of an increase in network lifetime.

III. NETWORK AND ENERGY MODEL ASSUMPTION

Multi hop Energy Efficient Heterogeneous Clustered (MEEHC) Scheme

- *n* sensor nodes are equally distributed in a square field
- All sensor nodes and the BS are fixed after they are deployed
- Transmission-receiving is based on multi-hop concept
- A WSN is made up of heterogeneous nodes with respect to node energy
- All sensors have identical importance
- CHs carry out data collection
- The BS is not energy restricted in association to energy of other nodes in the network

For the radio hardware energy dissipation the simplified first order radio model presented in [9] is used. In this model, the radio spends *Q* joules of energy (energy consumed in the electronics circuit) to operate the transmitter or receiver circuit. The ɽ and µ is the quantity of energy (in joules) per bit lost in the transmitter amplifier. Using the given radio model, the energy utilized

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$$E_{TL}=L\times(Q+\mu\times d^4)\ldots\ldots(1)$$

$$E_{TS}= L\times (Q+ ɽ \times d^2)\ldots\ldots(2)$$

Also the energy used in receiving the L-bit message is given by

$$E_{Rx}=L\times Q\ldots\ldots (3)$$

IV. OPTIMAL CLUSTERING

We consider an area ($A = M \times M$) square meters over which *n* nodes are evenly scattered and the BS is situated within the field for simplicity. Thus, the total energy lost in the network per round is given by following equation:
Following equation:

$$E_t=L\times(2\times n\times Q+n\times E_{DA}+ ɽ \times(k^2d^2_{BS}+n\times d^2_{CH})\ldots\ldots(4)$$

Differentiating above equation w.r.t k and equation to zero we can compute the optimal no. of clusters according to following equation

$$k_{opt}=\sqrt{\frac{n}{2\pi}}\sqrt{\frac{\tau}{\mu}}\frac{M}{d^2_{BS}}\ldots\ldots(5)$$

If the distance of a considerable percentage of nodes to the BS is greater than d_0 then

$$d^2_{BS}=\int_4 (x^2+y^2)\times\frac{1}{A}=.765\times\frac{M}{2}\ldots\ldots(6)$$

By using Equations (5) and (6), we derive the optimal probability of a node to become a CH, *popt*, which can be computed by (7).

$$p_{opt}=\frac{1}{.765}\times\sqrt{\frac{2}{n\pi}}\times\sqrt{\frac{\tau}{\mu}}\ldots\ldots(7)$$

A. *Cluster Head Election Mechanism*

The most favorable likelihood of a node to become a CH is a function of spatial density when nodes are regularly dispersed over the network. This clustering is optimal means energy usage is evenly distributed over all sensors and the total energy usage is less.

In MEEHC, three types of sensor nodes e.g., normal, advanced and super nodes are considered. Suppose E_0 is the energy at the start of each normal node, *m* is the fraction of superior nodes among normal nodes having α time more energy as compared normal nodes, and m_o is the fraction of super nodes among superior nodes having β times more energy than the normal nodes. A new heterogeneous setting does not influence on the spatial density of the network so the adjustment of p_{opt} does not change. Further, with the heterogeneous nodes the absolute energy of the network is changed as the original energy of each super node become E_0 (1 + β) and each superior node become E_0 (1 + α). Therefore, the total original energy of the new heterogeneous network setting is given by (8)

$$N\times\{(1-m)\times E_0+m\times(1-m_o)\times E_0\times(1+\alpha)+m\times m_o\times E_0\times(1+\beta)\}=n\times E_0\times(1+m\times(\alpha-m_o\times(\alpha-\beta)))\ldots\ldots(8)$$

Hence, the total energy of the system is improved by a factor of (1 + *m* (α - m_o (α - β))). The first improvement to the existing LEACH is to rise the epoch of the sensor network in proportion to the energy increment. In order to optimize the stable region of the system, the new epoch must become equal to (1/p_{opt}) x (1 + *m* (α - m_o (α - β))). Since the system has *m* (α - m_o (α - β)) times extra energy. If the similar threshold is put for super, advanced and normal nodes with the distinction that each normal node which belongs to *G* becomes a CH once every (1/p_{opt}) x (1 + *m* (α - m_o (α - β))) rounds per epoch, each super node which belongs to becomes a CH (1 + β) and each advanced node belonging to *G* becomes a CH(1 + α) times every(1/p_{opt}) x (1 + *m* (α - m_o (α - β))) rounds per epoch, then there is no assurance that the number of CHs per round per epoch will be p_{opt} x *n*. Therefore the restriction of p_{opt} x *n* CHs per round is dishonored. Requirement is to allocate a weight to the most favorable likelihood p_{opt}. This weight has to be equal to the remaining energy of each node divided by the mean original energy of that node. p_n, p_a and p_s is the weighted selection chance for normal nodes, advanced nodes, and for super nodes. *N*early there are (1 + *m* (α - m_o (α - β))) x *n* nodes with energy same as the original energy of a normal node. For maintaining the smallest amount energy expenditure in each round within an epoch, the mean number of CHs per round per epoch must be steady and equal to p_{opt} x n. In the heterogeneous scenario the average number of CHs (CH average) per round per epoch is given by (9).

$$CH_{average} = (1 + m \times (\alpha - m_0 \times (\alpha - \beta))) \times n \times p_n \quad (9)$$

The weighed probability for normal, advanced and super nodes is given by (10-12)

$$p_n = \frac{p_{opt}}{1 + m \times (\alpha - m_0 \times (\alpha - \beta))} \quad (10)$$

$$p_a = \frac{p_{opt}}{1 + m \times (\alpha - m_0 \times (\alpha - \beta))} \times (1 + \alpha) \quad (11)$$

$$p_s = \frac{p_{opt}}{1 + m \times (\alpha - m_0 \times (\alpha - \beta))} \times (1 + \beta) \quad (12)$$

In (1), by adjusting p_{opt} by the weighted probabilities of normal, advanced and super nodes to get new thresholds so that it can be used to choose the CH for each round. Substitute (9) in following(13), and we can get a new threshold for normal nodes which is given by (14).

$$T(s) = \begin{cases} \dfrac{p_{opt}}{1 - p_{opt} \times \left(r \bmod \dfrac{1}{p_{opt}} \right)} & if\ s \in G \\ 0 (otherwise) \end{cases} \quad (13)$$

$$T(s_n) = \begin{cases} \dfrac{p_n}{1 - p_n \times (r \times \bmod \dfrac{1}{p_n})} & if\ s \in G' \\ 0\ otherwise \end{cases} \quad (14)$$

where r is the current round, G is the set of normal nodes which are not chosen as CHs in the previous $1/pn$ rounds of the epoch, $T(sn)$ is the threshold applied to a population of n x (1 - m) normal nodes. This ensures that each normal node will be chosen as a CH accurately once every ($1/p_{opt}$) x (1 + m (α - m_o (α - β))) rounds per epoch, and that the mean number of CHs that are normal nodes per round per epoch is equal to n x (1 - m)xp_n. Likewise, thresholds for advanced and super nodes can also be computed. For the duration of this phase, every non-CH node has determined to link the nearby CH node. This choice is based on the established signal power of the announcement message. Following this the sensor node has to notify the CH node that it will be a associate of the cluster by distributing the short join message. Each sensor node forward this information back to the CH again using a CSMA MAC protocol.

V. PARTICLE SWARM OPTIMIZATION

The the PSO algorithm is an evolutionary computing technique, modeled after the social behavior of a flock of birds [51]. With reference of PSO, a swarm is a number of possible solutions to the optimization problem, where each probable solution is considered as a particle. The goal of the PSO is to obtain the particle position which produces the best computation of a given fitness function. In the starting procedure of PSO, each particle is set initial parameters randomly and is 'flown' all the way through the multi-dimensional explore space. During each production, each particle makes use of the information about its earlier best personal position and global best position to increase the likelihood of approaching towards a better solution space that will form in a better fitness. When fitness better than the individual best fitness is determined, it will be used to return the individual best fitness and revise its candidate solution according to the following equations

$$\begin{aligned} \boldsymbol{v_i(t+dt) = w * v_i(t) + c_1 * r_1} \\ \boldsymbol{* (p\ best_i - x_i(t)) + c_2} \\ \boldsymbol{* r_2(g\ best(t) - x_i(t), x_i(t+dt)} \\ \boldsymbol{= x_i(t) + v_i(t)dt} \end{aligned}$$

………………..(19)

TABLE(3.1): LIST OF VARIABLE USED IN PSO

V	VELOCITY OF THE PARTICLE
X	POSITION OF THE PARTICLE
T	TIME
C1,C2	LEARNING FACTORS(ACCELERATING) PARAMETERS
R1,R2	RANDOM NUMBERS BETWEEN 0 AND 1
PBEST	BEST POSITION OF THE PARTICLE
GBEST	GLOBAL BEST POSTION OF THE PARTICLE

W	INERTIA WEIGHT

A. *Fitness Function For PSO*

The main objective of the function is to optimize the combined effect of average distance from the sensors in a cluster, residual energy, node degree and head count (i.e. Number of times a sensor node served as cluster head). The fitness function, represented as $f(x_i(t))$ for the i_{th} particle is specified in the following equation:

12. Subject To

$$X_1 = \sum_{\substack{\forall n_j \in C_k \\ x_i \in S}} \left\{ \frac{\|n_j, x_i\|}{|C_k|} \right\}$$

$$X_2 = \sum_{\substack{i=1 \\ x_i \in S}}^{N} E(p_i) / \sum_{\substack{j=1 \\ n_j \in C_k}}^{|C_k|} E(n_j), E_{\min} \le E(n_j) \le E_{\max}$$

$$X_3 = N_{\deg}(p_i), 0 < \alpha_1, \alpha_2, \alpha_3 < 1$$

$$X_4 = 1/H(p_i), H(p_i) \ge 1, \text{ and } \alpha_1 \le \alpha_2 \le \alpha_3$$

In the given equation α1, α2, α3 are the influence parameters. In optimization function we supply relatively more assessment to the left over energy related with the particle pi. The sensor (n_j) have to have its energy level inside the range [emin, emax], or otherwise the node is filtered out and therefore it is not considered for similarity with other nodes in particle pi. Furthermore, e(pi), ndeg(pi) and h(pi) denotes the energy, node degree and head count related with the particle pi. Also, n_j is the jth node of kth cluster (ck) and |ck| represents the total number of nodes in the relevant cluster. The euclidean distance between node n_j and particle p_i is denoted by notation nj; xi. It is obvious from the equation that χ_1 is the mean distance of particle pi from all other sensors in the cluster and χ_2 is determine of particle energy relevant to other nodes. The χ_3 parameter represents to the node degree related with particle pi. This condition assists to choose the node about the particle with maximum degree. Furthermore, the number of neighbors for a sensor can be simply found by using the in-built commands of network simulator. The sensor which is linked to extra number of nodes shoes better competence in getting more packets effortlessly. X_4 is the possibility of selecting a node in particle pi on the foundation of its head count. The head count is essentially the occurrence of a node of suitable cluster head so far. Since the head count increases, the chance of its choice as cluster head reduces by definite degree. Lastly, at the end of each round (i.e. On completion of t_{max} number of generations),the particle whose parameters optimizes the objective function is selected as the global best position for the head node. The sensor nearby to the global best position is designated as the ch for the existing round. The elected node acts as ch until its energy goes down further than a certain level. Following which the current ch intimates n_{ca} to start the PSO calculation for the next round of cluster head selection.

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V. MODIFICATIONS TO PSO

There are three changes have been made in existing PSO to design a new algorithm called adaptive PSO. These changes are as follows;

A. First change

The entire search region is partitioned into number of segments like web of a spider. Therefore proposed algorithm produces starting population with evenly distributed solutions so that all the segments are having solutions. In the existing PSO initial populations were created at random where this population is at large extent dependent on the mutation operator. By splitting entire region into various segments search capacity of the modified algorithm is improved.

B. Second change

In the second change, there is more emphasis on sharing the available information. Each swarm uses information of its neighboring swarms having more favorable fitness value as compared to its own. The swarm having better fitness value may show path to other swarms. Because this algorithm does not take into account only the global positions as a result, there is very less probability to be indulged into local maxima. The concept is derived from the flocking nature of spiders. For example to find a minimum function 4 individuals are taken k, l, m, n. And their fitness values are represented

INDIVIDUALS	FITNESS VALUES
K	20
L	30
M	60
N	8

Table (3.2): Individual And Fitness Values

As per PSO particle n should traverse path p1 which is a directed graph. But particle l and m are having more favorable values as compared to n so particle must take information from l and m. As per the new generated algorithm particle n will traverse the path p2. The global

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optimum location might be at some place in region where particles l and m are present.

C. Third change

The new algorithm uses the fitness value to adjust the acceleration parameters c1 and c2 of the swarm. Level of interest in other swarms depends on the fitness value of the swarm. Ranking of swarm is based on their fitness values. In the original PSO there is no use of fitness values

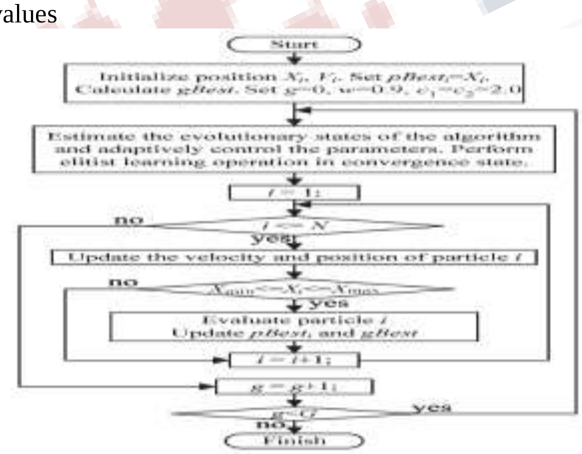
VI. VELOCITY UPDATE EQUATION OF A-PSO

vi =vi*wi + 1/rank(i)*r1()* (pbest(i)-xi) + social_info(i)i
xi = xi+ vi
where
social_info(i)
{
p=0
for each swarm j of the population
    if pfitness(j) is better than fitness(i)
    p = p + 1/rank(j) * r1() * (pbest(j)-xi);
if (p > vmax) return vmax;
else return p;
}

Pfitness(j) : best local fitness value seen by individual j.

Pfitness(i) : present fitness value of the swarm

Social_info() : provides the direction of the swarm by sharing information with swarms having better fitness values



Fig(3.5); Flow Chart Of A-PSO Algorithm

VII. SIMULATIONS AND RESULTS

A. Comparison Parameters

Average Packet delivery Ratio:

It is defined as follows:

$$Packet\ Delivery\ Ratio = \frac{Total\ received\ Packets}{Total\ generated\ Packets}$$

It is an important measure for computing the performance of the system. In the above formula the total generated packets is a combination of transmitted packets and packets lost in the network. As the Average packet delivery ratio in the figure increases we can conclude that the packets lost in the network decreases.

Table (4.1) Comparison of Packet Delivery Ratio

Simulation Time	Packet Delivery Ratio for PSO	Packet Delivery Ratio For A-PSO
0	0.8458	0.9352
10	0.8557	0.9048
20	0.8333	0.8920
30	0.8131	0.9092
40	0.8267	0.8889
50	0.8329	0.8875
60	0.8486	0.9269
70	0.8103	0.8923
80	0.8285	0.9010
90	0.8484	0.9103

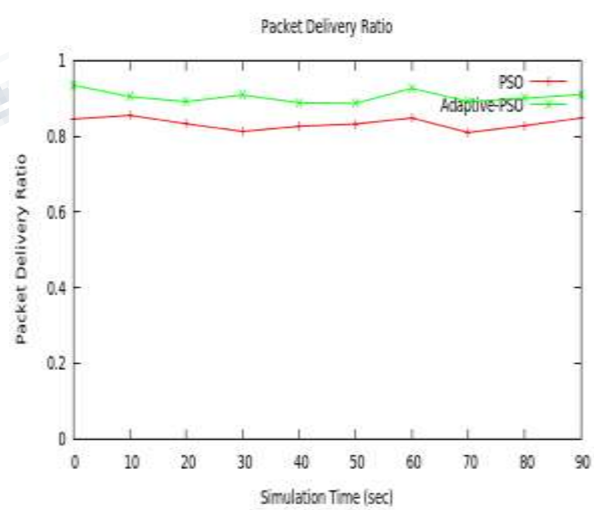


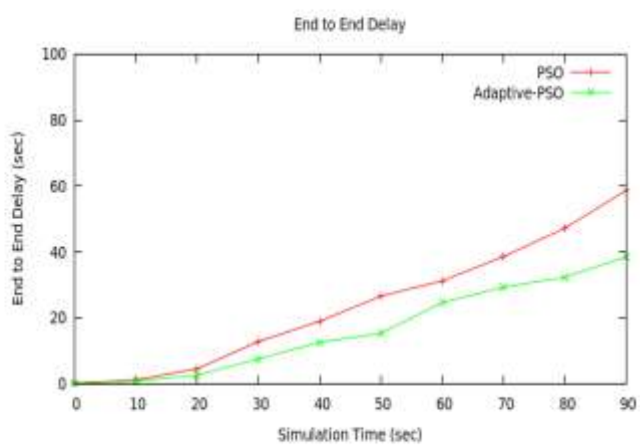
Fig.(4.1) Packet Delivery Ratio

B. Average End-to-End Delay:

It is defined as the total time taken by the packet to reach to the destination from the source from which it is generated. As the number of nodes in the network increases, the collision between packets in the network in case of base approach is greater than the proposed approach. As shown in the figure the delay in case of Adaptive PSO is less as compared to the PSO algorithm.

Table (4.2) Comparison for End-to-End Delay

Simulation Time(sec)	End to End delay(in sec)-PSO	End to End delay(in sec) -APSO
0	0.25	0.12
10	1.20	0.88
20	4.56	2.66
30	12.87	7.6
40	18.99	12.63
50	26.65	15.36
60	31.24	24.66
70	38.66	39.36
80	47.23	32.36
90	58.9	38.55



Fig(4.2): Average End to End Delay

C. Network Lifetime:

Network lifetime is a measure of the total time a node remains in the network. The energy consumed in the network decides the network lifetime of a node. The total energy consumed in the network while transmitting the data packet or while idle listening, protocol overhead and overhearing is termed as energy consumed by the network. The graph shows the residual energy of a node in the network and it is better in case of Adaptive PSO.

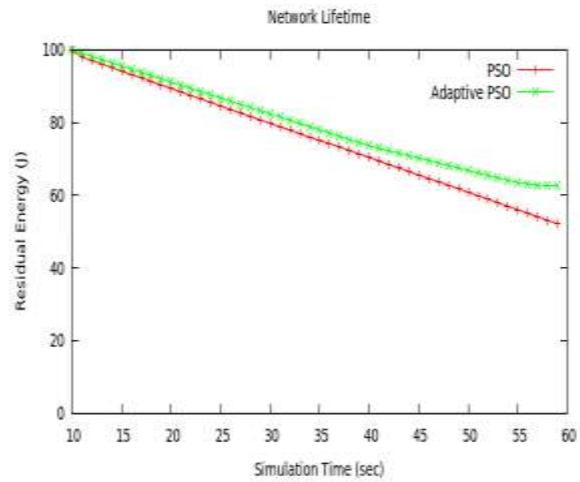


Fig.(4.3) Network Lifetime

Table (4.3) Simulation Parameters

Parameters	Values
Grid Area	800x800 sq. m
Channel Type	Wireless channel
Propagation Model	Two ray Ground
Queue Type	PriQueue
Queue Length	50
No of nodes	50
Initial Energy	100 j
Routing Protocol	AODV
c1,c2	2

VIII. CONCLUSION AND FUTURE SCOPE

In this project PSO has been modified to adaptive PSO. new algorithm generates initial population with a uniform distribution of solutions s.t every segment has a solution. dividing whole search space into segments improves the search capability of the proposed algorithm. there is large extent of sharing information. every swarm gather information from all swarms having better fitness value than its own. the new algorithm uses the fitness value to adjust the acceleration parameters c1and c2 of the swarm. level of interest in other swarms depends on the fitness value of the swarm. ranking of swarm is based on their fitness values. we can hope that a PSO will create an impact on the applications of PSO to real-world optimization and search problems. further work includes research into adaptive control of topological structures which is based on evolutionary state estimation (ese) and applications of the ese technique to other evolutionary computation algorithms.

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