Impact Factor (SJIF): 3.632

International Journal of Advance Research in Engineering, Science & Technology

e-ISSN: 2393-9877, p-ISSN: 2394-2444

(Special Issue for ITECE 2016)

Particle swarm optimization technique & optimization for reducing energy consumption in WSN by PSO

Prof. Bhaumik Machhi[1]

[1]Computer Science & Engineering, SLTIET

Abstract. A number of basic variations have been developed due to improve speed of convergence and quality of solution found by the PSO. On the other hand, basic PSO is more appropriate to process static, simple optimization problem. Modification PSO is developed for solving the basic PSO problem. The observation and review focusing on function of PSO, advantages and disadvantages of PSO, the basic variant of PSO, Modification of PSO and applications that have implemented using PSO. The application can show which one the modified or variant PSO that haven't been made and which one the modified or variant PSO that will be developed. Wireless sensor networks (WSN) is composed of a large number of small nodes with limited functionality. The most important issue in this type of networks is energy constraints. In this area several researches have been done from which clustering is one of the most effective solutions. The goal of clustering is to divide network into sections each of which has a cluster head (CH). The task of cluster heads collection, data aggregation and transmission to the base station is undertaken. In this paper, we introduce a new approach for clustering sensor networks based on Particle Swarm Optimization (PSO) algorithm using the optimal fitness function, which aims to extend network lifetime. The parameters used in this algorithm are residual energy density, the distance from the base station, intra-cluster distance from the cluster head. Simulation results show that the proposed method is more effective compared to protocols such as (LEACH, CHEF, PSO-MV) in terms of network lifetime and energy consumption.

Introduction

Theory of particle swarm optimization (PSO) has been growing rapidly. PSO has been used by many applications of several problems. The algorithm of PSO emulates from behavior of animals societies that don't have any leader in their group or swarm, such as bird flocking and fish schooling. Typically, a flock of animals that have no leaders will find food by random, follow one of the members of the group that has the closest position with a food source (potential solution). The flocks achieve their best condition simultaneously through communication among members who already have a better situation. Animal which has a better condition will inform it to its flocks and the others will move simultaneously to that place. This would happen repeatedly until the best conditions or a food source discovered. The process of PSO algorithm in finding optimal values follows the work of this animal society. Particle swarm optimization consists of a swarm of particles, where particle represent a potential solution. Recently, there are several modifications from original PSO. It modifies to accelerate the achieving of the best conditions. The development will provide new advantages and also the diversity of problems to be resolved. Study on the development of PSO is necessary to do to know how far its development, its advantages and disadvantages and how much use this method to settle a problem.

Variant of PSO

Exploration is the ability of a search algorithm to explore different region of the search space in order to locate a good optimum. Exploitation, on the other hand, is the ability to concentrate the search around a promising area in order to refine a candidate solution[3].With their exploration and exploitation, the particle of the swarm fly through hyperspace and have two essential reasoning capabilities: their memory of their own best position - *local best (lb)* and knowledge of the global or their neighborhood's best - *global best (gb)*. Position of the particle is influenced by velocity. In the original particle swarm optimization, there has also a lack of solution, because it is very easy to move to *local optima*. In certain circumstances, where a new position of the particle equal to global best and local best then the particle will not change its position. If that particle is the global best of the entire swarm then all the other particles will tend to move in the direction of this particle. The end of result is the swarm converging prematurely to a local optimum. If the new position of the particle pretty far from global best and local best then the velocity will changing quickly turned into a great value. This will directly affect the particle's position in the next step. For now the particle will have an updated position of great value, as a result, the particle may be out of bounds the search area. In analysis, PSO has advantages and disadvantages [4]. Advantages of the basic particle swarm optimization algorithm: PSO is based on the intelligence. It can be applied into both scientific research and engineering use. Then PSO have no overlapping and mutation calculation. The search can be carried out by the speed of the particle. During the development of several generations, only the most optimist particle can transmit information onto the other particles, and the speed of the researching is very fast. After that the calculation in PSO is very simple. Compared with the other developing calculations, it occupies the bigger optimization ability and it can be completed easily. The last one is PSO adopts the real number code, and it is decided directly by the solution. The number of the dimension is equal to the constant of the solution. On the other hands, disadvantages of the basic particle swarm optimization algorithm are the method easily suffers from the partial optimism, which causes the less exact at the regulation of its speed and the direction. Then the method cannot work out the problems of scattering and optimization and the method cannot work out the problems of non-coordinate system, such as the solution to the energy field and the moving rules of the particles in the energy field.

Modification of PSO

The modification in PSO consists of three categories: extension of field searching space, adjustment the parameters, and hybrid with another technique. The modifications of PSO can enhance its performance.

a. Single Solution PSO

A large number of PSO variations can be found to locate single solutions. These PSO implementations were specially developed to obtain single solutions to continuous-valued, unconstrained, static, single-objective, optimization problem, most of these algorithm can also be applied to other problem types.

b. Niching with PSO

In the EC field, algorithms that locate multiple solutions are refers to as niching algorithm. The process of finding multiple solution or niche is generally referred to as speciation. Niching algorithms model yet another natural process, where large numbers of individuals compete for the use of limited resources on physical environment. Nieces are partitions of an environment while species are partitions of computational optimization, a niece represents one solutions to the problem, while a species refers to the group of individuals (particle in the context of PSO) that convergence on a single niece.

c. Constraint Optimization using PSO

Constraint reduces the feasible space where in solution to the problem can be found. Optimization algorithms need to ensure that a feasible solution is found. That is the optimization algorithm should find a solution that both optimizes the objective function satisfies all constraints. If it is not possible to satisfy all constrains, the algorithm has to balance the trades off between optimal objective function value and number of constrain violated

d. Multi-objective optimization with PSO

Many real world optimization problems require the simultaneous optimization of a number of objectives (multi-objectives). The main objective of MOO algorithms is to find a set of solution which optimally balance the trade-offs among the objective of a MOP. It is different with the basic PSO that return only one solution.

e. Dynamic Environment With PSO

In dynamic Environments, PSO should be fast to allow quick re-optimization. It is desirable to find a good solution before the next environment change. In original PSO, it is impossible to convergence to an equilibrium state in its first goal to locate the optimum. There are several solutions for dynamic environment. Such as: a. Environment change detection, It is to allow timeout and efficient tracking of optimum, b. Response to environment changes, c. Changing the inertia weight update, d. Reinitialize Particle Solution, e. Limit Memory, f. Local Search, g. Split adaptive PSO, h. Fine-Grained, i. charged Swarm.

f. Discrete PSO

PSO was originally developed for continuous-valued spaces. Many problems are however, defined for discrete value. Fortunately, the PSO is easily adaptable to discrete-value spaces.

Observation and Review

Particle swarm optimization (PSO) is a biologically inspired computational search and optimization method developed in 1995 by Eberhart and Kennedy based on the social behaviors of birds flocking or fish schooling. Recently, there are many variants of PSO, and it may always grow rapidly. Figure 1 describes the variants of particle swarm. We have considered that velocity clamping, inertia weight, constriction coefficient, synchronous and asynchronous updates are the basic variations of PSO that have been developed to improve speed of convergence and quality of solution found by the PSO. Figure 2 presents distribution of articles in terms of basic variant of PSO. Regarding on this inertia weight has the largest number of literatures between 2006 and 2010. Due to the progress of variant PSO is rather new, so there is only a few articles that has made. Every basic variant of PSO has utility that will cover shortfall of PSO. In addition they also have advantages and disadvantages as shown in the table below:

Basic Variant	Function	Advantages	Disadvantages
Velocity Clamping	Control the global exploration of the particle reduce the size of the step velocity, so that the particles remain in the search area, but it cannot change the search direction of the particle	VC reduce the size of the step velocity so it will control the movement of the particle	If all the velocity becomes equal to the particle will continue to conduct searches within a hypercube and will probably remain in the optima but will not converge in the local area.
Inertia weight	Control the momentum of the particle by weighing the contribution of the previous velocity.	A larger inertia weight in the end of search will foster the convergence ability.	Achieve optimality convergence strongly influenced by the inertia weight
Constriction Coefficient	To ensure the stable convergence of the PSO algorithm	Similar with inertia weight	when the algorithm converges, the fixed values of the parameters might cause the unnecessary fluctuation of particles
Synchronous and Asynchronous Updates	Optimization in parallel processing	Improved convergence rate	Higher throughput: More sophisticated finite element formulations Higher accuracy (mesh densities)

Table1. The Basic Variant of PSO

particle swarm optimization is used to solve statics problem. For solving another form of problem, many researchers have developed variant PSO, such as: Single Solution, Niching with PSO, Constraint Optimization using PSO, Multi-objective optimization, Dynamic Environment and Discrete PSO. Every variant of PSO have different form and function. Each of them also has variety methods to solve their problem. Table 2 describes every characteristics of basic variant of PSO. There are many researchers that have develop many application using modification PSO. Figure 3 presents distribution of articles in terms of modification of Particle Swarm Optimization. The number of papers using single solution PSO yields a peak in 2007 and decreases gradually after that. Niching with PSO is only used by some of researchers. From the figure below, dynamic environment of PSO and multi-objective With the characteristic of modification of PSO, there are several application areas that can develop, such as scheduling, searching, forecasting, feature selection, classification, Modification of particle swarm optimization problems have implemented in several areas, i.e. Searching, Optimization production rate and functions problem.

Variant PSO	Utilities	Methods
Single Solution of PSO	Obtain single solutions to continuous-valued, unconstrained, static, single-objective, optimization problem	Social network structure, hybrid algorithm, sub swarm-based, revealing methods, mimetic PSO multi-start PSO
Niching with PSO	Niching (speciation) techniques have the ability to locate multiple solutions in multimodal domains	Quasi-sequential niching, Parallel niching algorithm, Objective function stretching, Sequential niching
Constraint Optimization using PSO	Find a solution that both optimizes the objective function satisfies all constraints. If it is not possible to satisfy all constrains, the algorithm has to balance the trades off between optimal objective function value and number of constrain violated	convert to unconstrained problem, Repair method, Boundary constrain, Pareto ranking, Preserving feasible
Multi-objective optimization (MOO)	Find a set of solution among the objective of a multi optimization problem.	Criterion-based methods, dominance-base.
Dynamic Environment of PSO	Have an ability to solve an optimization in the dynamic real-world problems although if it is in multi objective optimization	Environment change detection, Response to environment changes, Changing the inertia weight update, Reinitialize Particle Solution, Limit Memory, Local Search, Split adaptive PSO, Fine-Grained, Charged Swarm
Discrete PSO	Find an optimization problem that operate on binary search space	Binary PSO, General Discrete PSO

Table 2.Characteristic Modifications of PSO

PSO clustering problem

Two main problem of clustering using PSO method is the convergence to local optimal and slow convergence velocity, which is tried to be solved by using two ideas of chaos theory and acceleration strategy . Updating velocity of the cluster centers is done for each particle for relocating the particle to the new position, from the best answer for each particle (Pbest) and the best global solution so far (gbest) . In which **W** Inertia coefficient rate tends to previous velocity of the particle, $c_1$ratestends to the best local position of the particle, and c_2 trends to the best global position of the particle.

Cr random value is created for each round independently between 0 and 1.which substitutes both **r1** and **r2**,and parameter k is the number of predicted clusters. Using the chaos theory in PSO population generation will result in more diverse of the algorithm. As can be seen in Figure 1. To achieve more optimal particle swarm optimization algorithm, chaos theory is applied And in other change to increase the rate of convergence used acceleration strategy therefore in this mode a number of the population which are the best toward the target move not all population that it increases the rate of convergence [17].

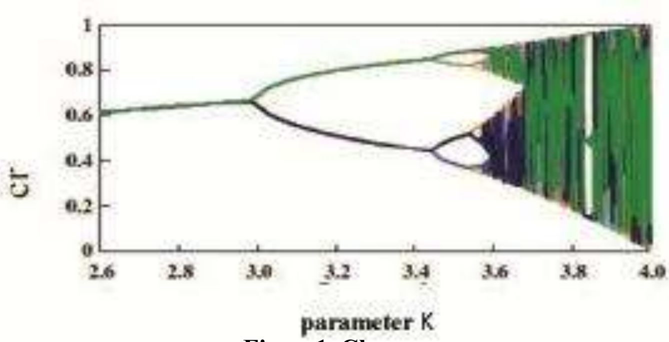

Figure1. Chaos map

Proposed Method

Our proposed algorithm is composed of two clustering and data transmission phases.

Clustering Phase

In clustering phase, the particles are generated randomly. Then the best points are selected as the cluster heads and other nodes which are located near each cluster head becomes the member of the cluster and then fitness function is calculated for every cluster heads. If the fitness function is better than global best it is substituted. This process is done for 1000 generation. Then each node prepares a control message that contains identity and value of its residual energy and sends it directly to the base station .The base station which receives the information performs clustering operation.

Proposed Validation index

As previously mentioned, the clustering is more desirable in which intra-cluster density is higher and in another word, the clusters are more cohesive and inter-cluster density is lower. Based on this principle, in the proposed method to estimate the optimal number of clusters. The first Select the number of clusters. Also to measure rate of clusters separation the different distance between cluster than total center of data set for the number of clusters considered, and then calculated the ratio between two, since the clustering is more desirable. The clusters are more compact and farther apart So, for the number of clusters where the index is maximum the clustering is more desirable and the optimal number of clusters is achieved. Validation index is composed of two parts, F1 and F2. Whatever the amount of the above criterion is greater clustering is better.

Inter: inter-cluster distance for which farther is better.

Intra: intra-cluster distance for which closer is better.

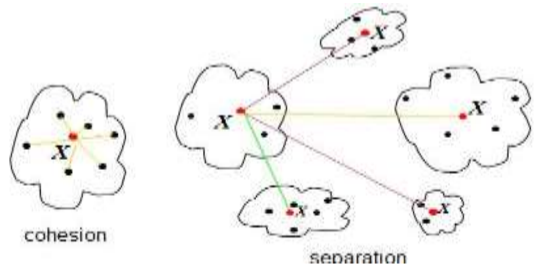

Figure2.Performance of the proposed index

Eq. (9),(10) denotes the intra and inter cluster separation:

$$\text{Intra(c)} = \sum_{i=1}^{c}\sum_{j=1}^{N}(Xj - Xi) \quad (9)$$

In Eq. (9) the total distance between nodes in each cluster and its cluster head calculated in which **c** is the number of clusters, **N** is the number of nodes, $\mathbf{X_j}$ is the cluster head and **Xi** denotes the distance of the nodes from its relative cluster head. The intra cluster separation is shown in the following equation:

$$\text{Inter(c)} = \sum_{j=1}^{c}(Xj - X) \quad (10)$$

To calculate the inter clusters separation, the distance between the centers of the clusters and the center of total data set is calculated. For cluster range specified the amount of this index calculate and show in chart. In the conditions in which the slope of the curve is sharper the estimate of the number of clusters is more accurate.

Data transmission phase

After cluster formation and cluster heads election of each cluster data can be transmitted by the normal nodes to corresponding cluster heads. In this phase, each normal node is connected to the nearest cluster head. Cluster heads are assigned with the implementation of a TDMA schedule to each cluster member. Each node in the allocated interval sends its data to cluster head in the form of data message. The cluster heads aggregate and transmit data towards base station after receiving all messages from cluster member nodes. Then the energy consumption of all nodes is computed.

The transmission phase is as follows:

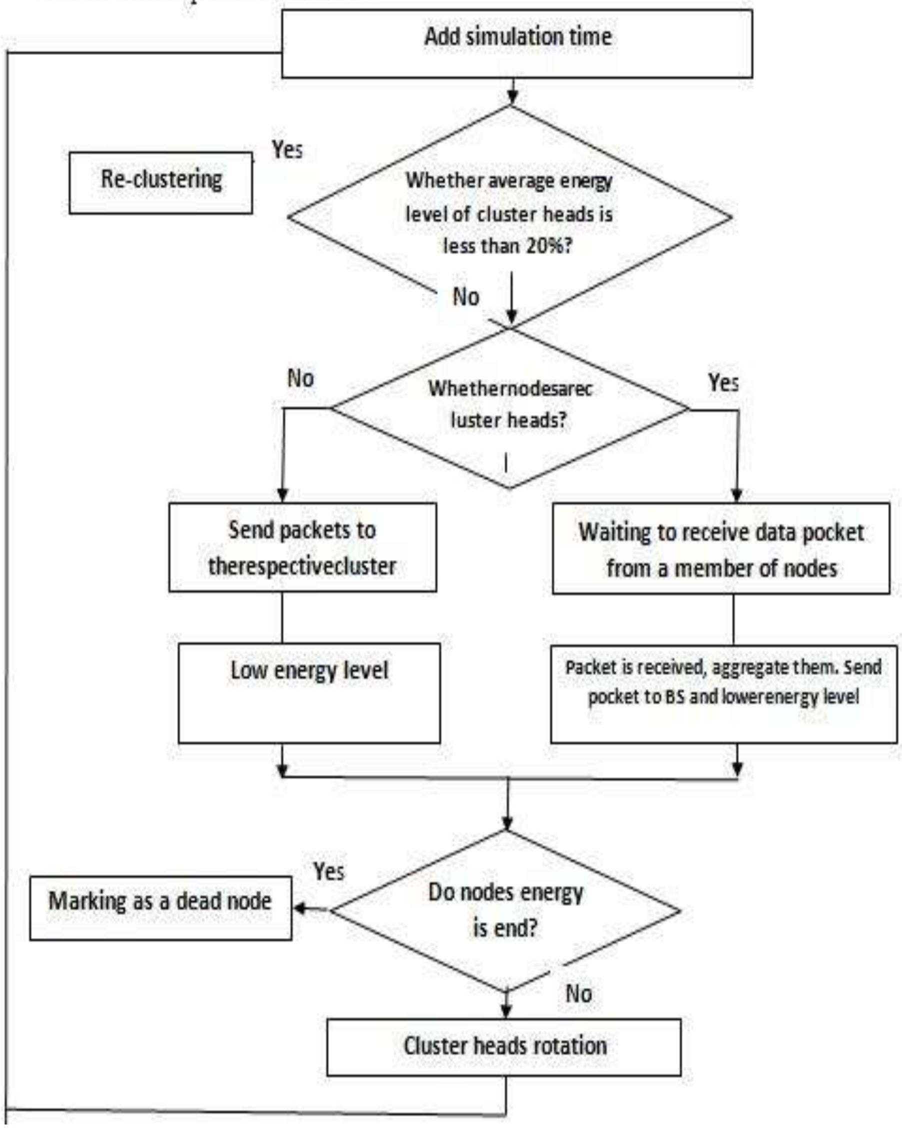

Figure 3. Data transmission phase flowchart

Simulation

The algorithm is simulated using MATLAB software. The parameters used are noted in the table 3. j_ and j_ are electronic energies, and EDA is the energy needed for data aggregation at cluster heads.

Parameter	Value
j__	10 pJ/bit/m2
j_	0.0013 pJ/bit/m4
Eelec	50/nJ/bit
EDA	5/nJ/bit/signal
Initial energy per node	0.5 j
Data packet size	4000 bit
Control packet size	200 bit

Table 3.simulation parameters

The first step of our purpose approach is that using PSO to find the most optimal points in area and then the closest node to it are consider as cluster heads. we have 100 × 100 area with 100 nodes randomly dispersed and also the base station is put on the 50 × 50 coordinates. The number of particle and the velocity is calculated with respect to the area size. Initially, minimum particles together work is equal 20-bit and The velocity initially is equal to 4 which was comparative and by increase the number of current nodes in the environment are changed. The most influential parameters in the calculation of PSO are values that must be consider for **c1, c2, w**, which in more papers are considered as **c1 = c2 = 2** and **w = 1**. But to find more accurate values due to their significant impact on the problem solution, we evaluated all possible values between different intervals. After 1000 generations, with the cooperation of 20 particles together, as you can see in Figure 4 the best value for the parameter is equal **to c1=c2=0.5** and **w=0.007.**

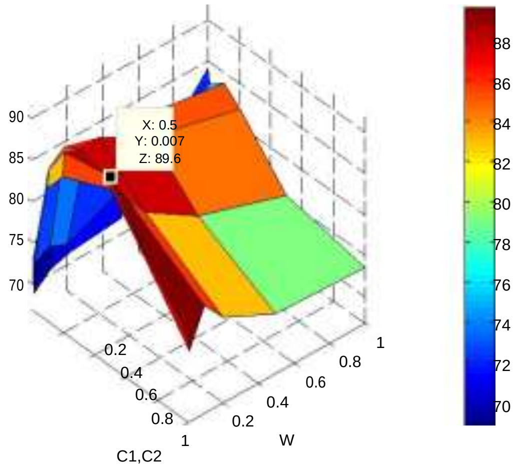

Figure 4. The parameter values c1,c2, w

As the result of the random motion, the particles may be out of the environment that are required to move back into environment. We apply the support vector machine(SVM) supervised learning method to return the particle into the environment [22].

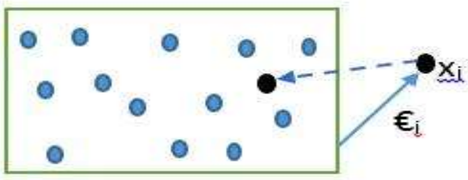

Figure 5: represents a range of educational particles

In Fig 5, there is a X_i particles outside the range that with ξi**(**st > v**)** is returned into the environment where compared to moving the particle on the border better results will be achieved. The next important issue is the value that should be considered for alpha. When the node energy is less than alpha value the cluster head is replacement. To consider the optimal alpha value all values between 0 and 1 with the distance of the 0.1 are considered. After running four times and averaging, the best alpha value for 100 nodes is equal to 0.8 and for 200 nodes is equal to 0.4 which can be seen in Figure 6.

3000

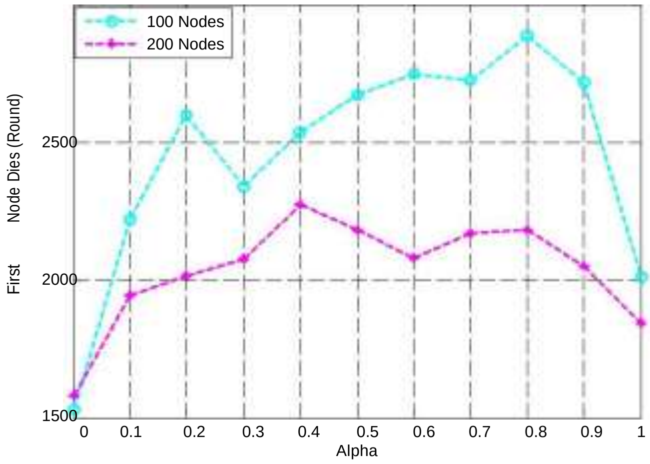

Figure 6. Alpha value in two cases of 100 nodes and 200 nodes

As you can see in Figure 7 that cluster heads are suitably dispersed. A point that should be noted is that the nodes that are close to the base station and its distance to the nearest cluster heads is less, transmit data directly to the base station and reduce energy consumption considerably.

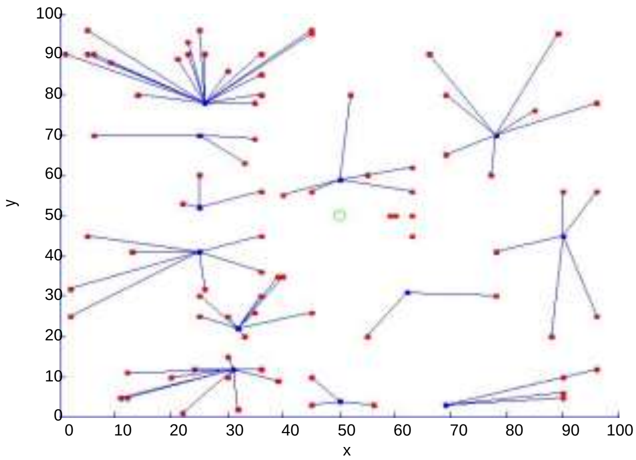

Figure 7.The number of nodes associated to each cluster

We compared the proposed algorithm with the LEACH, CHEF, PSO-MV, GFCM algorithms which results are as follows. Figure 8 shows the rate of dead nodes and network lifetime after implementing the proposed protocols which is higher compared to LEACH, CHEF, PSO-MV, GFCM protocols, which increases networks lifetime.

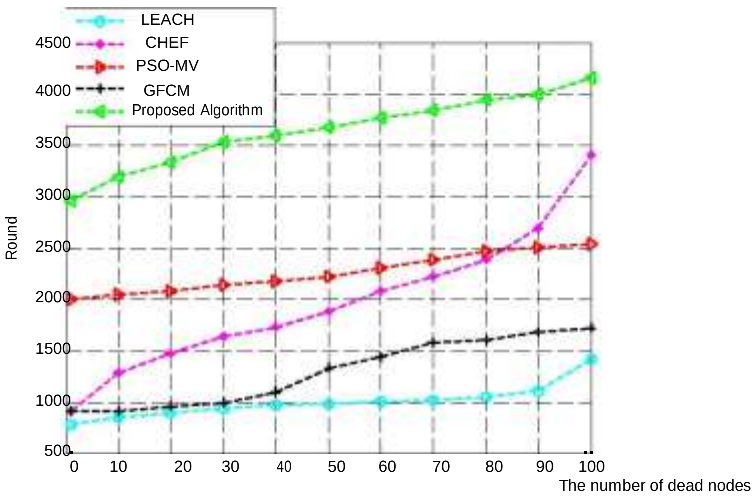

Figure 8. Comparing the proposed algorithm with four efficient algorithms, namely LEACH, CHEF, PSO-MV, GFCM in terms of the number of dead nodes

As shown in Figure 10 the first node in the LEACH algorithm dies at 790th round and the last dies at 1420th round, while using the proposed algorithm the first node dies in round 2959 and the last node dies in the 4150th round which is due to the selection of the best possible cluster heads. Figure 11 denoted the energy consumed by LEACH, CHEF, PSO-MV, GFCM protocols and the proposed algorithm in which the proposed protocol has significantly lower total energy consumption than the other protocols.
As you can see in Figure 9 the slope of the proposed algorithm is softer and suitable than that of the LEACH algorithm which lead to slower energy discharge. Therefore in LEACH **5%** of energy is lost in the 98th round and total energy is finished in the 1238th round While using the proposed algorithm, **5%** of energy is lost in the 233rd round and total energy is finished in the 3971st round, which increases of network lifetime.

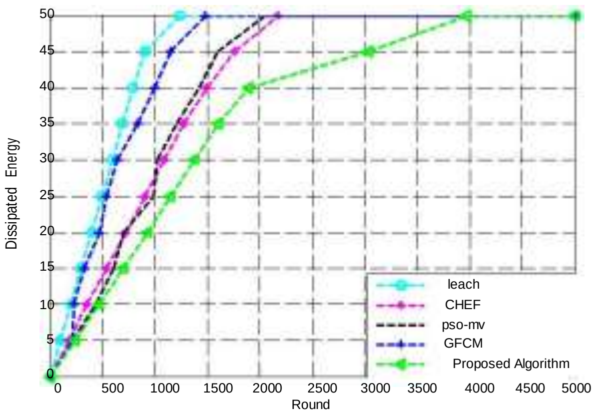

Figure 9. Comparing the proposed algorithm with four efficient algorithms, namely LEACH, CHEF, PSO-MV, GFCM in terms of total energy consumption

Conclusions

In this paper, we have made review of the different methods of PSO algorithm. Basic particle swarm optimization has advantages and disadvantages, to overcome the lack of PSO. There are several basic variant of PSO. The modified variant PSO help the PSO to process other conditions that cannot be solved by the basic PSO. The observation and review is made to show the absolute function of PSO, advantages and disadvantages of PSO, the basic variant of PSO, Modification of PSO. we introduce a new approach for sensor network clustering using Particle Swarm Optimization (PSO) algorithm. The parameters which are used in the algorithm are residual energy, density, distance from the base station, intra-cluster distance and cluster heads distance from each other. Our goal was to propose a new cost function to select the best cluster heads that combine the various criteria affecting the energy efficiency of cluster heads and cluster heads rotation among the nodes. Also, using the proposed algorithm the network coverage is evaluated and compared with some previous methods which have proved better performance and improved network lifetime and energy consumption.

References

[1] Akiyldiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, A survey on sensor networks, IEEE Communication Magazine, vol 40, 2002,pp 102–114.

[2] G. Pottie and W. Kaiser, Wireless integrated sensor networks(WINS), Communications of the ACM, vol. 43, no. 5 , 2000,pp. 55-58.

[3] G.Hill, R. Szeweyk , A. Woo, D. Culler, S. Hollar, and K.Pister, System architecture directions for networked sensors, in proceedings of the International Conference on Architectural Support for programming Languages and Operating Systems (ASPLoS IX). Cambridge, MA, 2000,pp. 93-104.

[4] W. Merrill, K. Sohrabi, L. Girod , j. Elson , F. Newberg ,and W. Kaiser, Open standard development for distributed sensor networks, in Proceedings of SPIE Unattended Ground Sensor Technologies and Applications IV, Orlando, FL.2002,pp,327-337.

[5] J. M. Kim, S.H. Park, Y.J. Han, T.M. Chung, CHEF: cluster head election mechanism using fuzzy logic in Wireless Sensor Networks, in: International Conference of Advanced Communication Technology, 2008, pp. 654–659.

[6] N. Eghbali, Performance Improvement of Information Dissemination Protocols in Sensor Networks Through Data Aggregation, Computer Engineering and Information Technology Department, 2007. PP 1-121.

[7] W. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy Efficient Communication Protocol for Wireless Micro sensor Networks (LEACH), Proceedings of 33rd hawaii international conference systems science - vol.8,2004, pp 3005-3014.

[8] M. Handy , M. Haase , and D. Timmermann, Low energy adaptive clustering hierarchy with deterministic cluster – head selection , in proceeding of IEEE, International Conference on Mobile and wireless Communications networks, Stockholm, Sweden,2002, pp. 368-372.

[9] V. Handziski, A. Kopke, H. Karl, C. Frank, W. Drytkiewicz, Improving the Energy Efficiency of Directed Diffusion Using Passive Clustering," European Workshop on Wireless Sensor Networks 2004 , pp. 172–187.

[10] O. Younis and S. Fahmy, HEED: A hybrid, energy efficient, distributed clustering approach for adhoc sensor networks, IEEE Transactions on Mobile Computing,vol.3,no.4,2004,pp.366-379.

[11] V. Loscrì, G. Morabito, S. Marano, A Two-Levels Hierarchy for Low-Energy Adaptive Clustering Hierarchy, in proceeding of IEEE 2005,pp. 1809-1813.

[12] S. Hussain, A.W. Matin, and O. Islam. Genetic algorithm for energy efficient clusters in wireless sensor networks. In Fourth International Conference on Information Technology,2007,pp147–154.

[13] D. kumar, T. C. Aseri and R. B. Patel EEHC: Energy efficient heterogeneous clustered scheme for wireless sensor networks, Computer Communications, vol 32,2009,pp.662-667.

[14] K. LingaRaj, D. Aradhana and Nagaveni B.Biradar. Multiple mobile agents in wireless sensor networks using genetic algorithms. International Journal of Scientific and Engineering Research, vol3,2012, pp1–5.

[15] H.Yua, W. Xiaohuia PSO-based Energy-balanced Double Cluster-heads Clustering Routing for wireless sensor networks ,Procedia Engineering, vol 15 ,2011, pp.3073 – 3077.

[16] S.-H. Hong, B.-K. Kim and J.-M. Gil An Algorithm for an Energy-Efficient Smart Sensor with EECS Routing Protocol in Wireless Sensor Networks, Springer Science Business Media Dordrecht 2012, pp. 685–692.

[17] Li-Yeh Chuang a, Chih-Jen Hsiao b, Cheng-Hong Yang, Chaotic particle swarm optimization for data clustering, Elsevier, 2011. PP 109-115.

[18] S.M. Guru, S.K. Halgamuge, and S. Fernando. Particle swarm optimizers for cluster formation in wireless sensor networks. In Proceedings of the International Conference on Intelligent Sensors, Sensor Networks and Information Processing,2005,pp 319–324.

[19] J. Hou, X. Fan, W. Wang, J.Jie, and Y. Wang. Clustering strategy of wireless sensor networks based on improved discrete particle swarm optimization. In The Sixth International Conference on Natural Computation (ICNC), vol 7,2010,pp3866–3870.

[20] B.Solaiman , A. Sheta , Computational Intelligence for Wireless Sensor Networks: Applications and Clustering Algorithms, International Journal of Computer Applications ,Vol 73 ,2013, pp0975 - 8887.

[21] S . He , Y , Dai , R , Zhun , S , Zhao , A Clustering Routing Protocol for Energy Balanc of WSN based on Genetic Clustering Algorithm , International Conference on Future Computer Supported Eduction ,2012, pp 788-793

[22] J.Weston and C. Watkins, Multi-class support vector machines, Technical Report CSDTR Department of Computer Science, Royal Holloway, University of London, Egham, 1998, pp98-104.