IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

Particle Swarm Optimized Distributed Energy Efficient Clustering Protocol for WSN

Afroz Mansoori
afaroz.mansoori@gmail.com

Abstract – **Wireless sensor networks are an emerging technology for monitoring physical world. The energy constraint of Wireless sensor networks makes energy saving and Prolonging the network lifetime become the most important goals of various routing protocols.**

Different energy efficient clustering protocols for heterogeneous wireless sensor networks and compares these protocols on various points like, location awareness, clustering method, heterogeneity level and clustering Attributes. Energy efficient clustering protocols should be designed for the characteristic of heterogeneous wireless sensor networks. Many issues in WSNs are formulated as multidimensional optimization problems, and approached through bio-inspired techniques. Particle swarm optimization (PSO) is a simple, effective and computationally efficient optimization algorithm. It has been applied to address WSN issues such as optimal deployment, node localization, clustering and data-aggregation.

Keywords – **wireless sensor network, clustering protocol, energy efficient, heterogeneous network, and particle swarm optimization.**

I. Introduction

A collection of mobile or static nodes which are able to communicate with each other for transferring data more efficiently and autonomously can be defined as wireless sensor network. A lot of applications of wireless sensor network can be found in different field such as events, battlefield surveillance, recognition security, drug identification and automatic security [1].

In wireless sensor network, one of the main constraints is limited battery power which plays a great influence on the lifetime and the quality of the network. Several routing protocols have been designed for wireless sensor networks to satisfy energy utilization and efficiency requirement. Efficiency, scalability and lifetime of wireless sensor network can be enhanced using hierarchical routing. Here, sensors are organized themselves into clusters and each cluster has a cluster head [1].The main role of cluster head is to provide data communication between sensor nodes and the base station efficiently[2].

Another way to prolong the lifetime of wireless sensor network is to insert a percentage of heterogeneous nodes. Heterogeneous wireless sensor network consists of sensor nodes with different ability, such as different computing power and sensing range. Heterogeneous wireless sensor networks are very much useful in real deployments because they are more close to real life situations [3, 4].

There are two types of clustering techniques. The clustering technique applied in homogeneous sensor networks is called homogeneous clustering schemes, and the clustering technique applied in the heterogeneous sensor networks is referred to as heterogeneous clustering schemes.

Bio-inspired optimization methods are computationally efficient alternatives to analytical methods. Particle swarm optimization (PSO) is a popular multidimensional optimization technique. Ease of implementation, high quality of solutions, computational efficiency and speed of convergence are strengths of PSO. Literature is replete with applications of PSO in WSNs. Our Objective is to give a flavour of PSO to researchers in WSN, and to give a qualitative treatment of optimization problems in WSNs to PSO researchers in order to promote PSO in WSN applications.

Many existing clustering techniques such as LEACH consider homogeneous sensor networks where all sensor nodes are designed with the same battery energy. The energy saving schemes for

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

homogeneous wireless sensor networks do not perform efficiently when applied to heterogeneous wireless sensor network. Thus, Energy efficient clustering protocols should be designed for the characteristic of heterogeneous wireless sensor networks [3]. Paradigm of heterogeneous wireless sensor network and impact of heterogeneous resources are discusses in [4, 5]. The set of attributes that can be used to categorize and differentiate clustering protocols of heterogeneous wireless sensor networks are discussed in papers [4, 6].

A. *HEED Protocol*

Assume that there are N sensor nodes, which are randomly dispersed within a 100m*100m square region (Figure 1). Following assumptions are made regarding the network model is:

1. Nodes in the network are quasi-stationary.
2. Nodes locations are unaware i.e. it is not equipped by the GPS capable antenna.
3. Nodes have similar processing and communication capabilities and equal significance.
4. Nodes are left unattended after deployment.

Cluster head selection is primarily based on the residual energy of each node. Since the energy consumed per bit for sensing, processing, and communication is typically known, and hence residual energy can be estimated. Intra cluster communication cost is considered as the secondary parameter to break the ties. A tie means that a node might fall within the range of more than one cluster head.

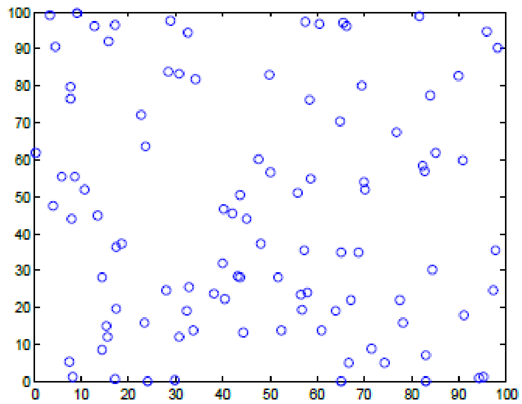

Figure1.Random Deployment of 100 Sensor Nodes

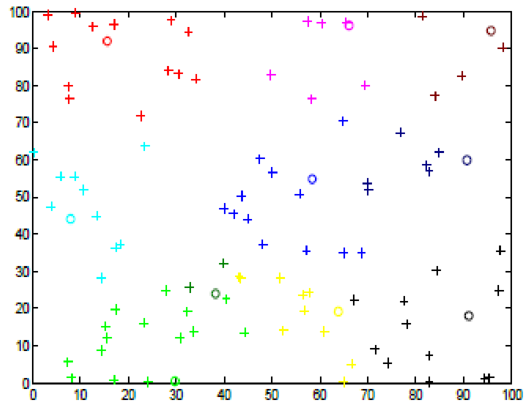

Figure2.Clusters Formation by HEED protocol

When there are multiple candidate cluster heads, the cluster head yielding lower intra-cluster communication cost are favored. The secondary clustering parameter, intra-cluster communication cost, is a function of (i) cluster properties, such as cluster size, and (ii) whether or not variable power levels are permissible for intra-cluster communication. If the power level used for intra-cluster communication is fixed for all nodes, then the cost can be proportional to (i) Node Degree, if the requirement is to distribute load among cluster heads, or if the requirement is to distribute load among cluster heads, or (ii)1/Node Degree , if the requirement is to create dense clusters. This means that a node joins the cluster head with minimum degree to distribute cluster head load or joins the one with maximum degree to create dense clusters.

Each node performs neighbor discovery, and broadcasts its cost to the detected neighbors. Each node sets its probability of becoming a cluster head, *CHprob*, as follows:

$$CHprob = max\left(Cprob * \left(\frac{Eresidual}{Emax}\right), pmin\right)$$

Where, *Cprob* is the initial percentage of cluster heads among n nodes, while *Eresidual* and *Emax* are the residual and the maximum energy of a node (corresponding to the fully charged battery), respectively. The value of *CHprob* is not allowed to fall below the threshold *pmin*. The clusters formation by HEED protocol is shown in figure 2.

IJDACR
International Journal Of Digital Application & Contemporary Research
International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

B. DEEC Protocol

In this section, we present the detail of our DEEC protocol. DEEC uses the initial and residual energy level of the nodes to select the cluster-heads. To avoid that each node needs to know the global knowledge of the networks, DEEC estimates the ideal value of network life-time, which is use to compute the reference energy that each node based on residual should expend during a round.

Cluster-head selection algorithm energy

Let n_i denote the number of rounds to be a cluster head for the node s_i, and we refer to it as the rotating epoch. In homogenous networks, to guarantee that there are average poptN cluster-heads every round, LEACH let each node si (i = 1, 2. . . N) Becomes a cluster-head once every n_i = $1/p_{opt}$ rounds. Note that all the nodes cannot own the same residual energy when the network evolves.

If the rotating epoch n_i is the same for all the nodes as proposed in LEACH, the energy will be not well distributed and the low-energy nodes will die more quickly than the high-energy nodes. In our DEEC protocol, we choose different n_i based on the residual energy Ei(r) of node si at round r. Let pi = $1/n_i$, which can be also regarded as average probability to be a cluster-head during n_i rounds. When nodes have the same amount of energy at each epoch, choosing the average probability pi to be p_{opt} can ensure that there are p_{opt} N cluster-heads every round and all nodes die approximately at the same time. If nodes have different amounts of energy, pi of the nodes with more energy should be larger than p_{opt} . Let E(r) denote the average energy at round r of the network, which can be obtained by,

$$\bar{E}(r) = 1/N \sum_{i=1}^{N} E_i(r) \qquad 1$$

To compute E(r) by Eq. (1), each node should have the knowledge of the total energy of all nodes in the network.

We will give an estimate of E(r) in the latter subsection of this section. Using E(r) to be the reference energy, we have

$$P_i = P_{opt}\left[1 - \frac{\bar{E}(r) - E_i(r)}{\bar{E}(r)}\right] = P_{opt}\frac{E_i(r)}{\bar{E}(r)} \qquad 2$$

This guarantees that the average total number of cluster heads per round per epoch is equal to:

$$\sum_{i=1}^{N} P_i = \sum_{i=1}^{N} P_{opt}\frac{E_i(r)}{\bar{E}(r)} = P_{opt}\sum_{i=1}^{N}\frac{E_i(r)}{\bar{E}(r)} = NP_{opt} \qquad 3$$

It is the optimal cluster-head number we want to achieve. We get the probability threshold, that each node s_i use to determine whether itself to become a cluster-head in each round, as follow

$$T(s_i) = \begin{cases} \dfrac{P_i}{1 - P_i\left(r \bmod \dfrac{1}{P_i}\right)} & if\ s_i \epsilon G \\ 0 & otherwise \end{cases} \qquad 4$$

Where, G is the set of nodes that are eligible to be cluster heads at round r. If node s_i has not been a cluster-head during the most recent n_i rounds, we have s_i 2 G. In each round r, when node s_i finds it is eligible to be a cluster-head, it will choose a random number between 0 and 1. If the number is less than threshold T (s_i), the node si becomes a cluster-head during the current round.

Note the epoch n_i is the inverse of P_i. From Eq. (4), n_i is chosen based on the residual energy Ei(r) at round r of node s_i as follow

$$n_i = \frac{1}{P_i} = \frac{\bar{E}(r)}{P_{opt}E_i(r)} = n_{opt}\frac{\bar{E}(r)}{E_i(r)} \qquad 5$$

Where n_{opt} = $1/P_{opt}$ denote the reference epoch to be a cluster- head. Eq. (5) shows that the rotating epoch n_i of each node fluctuates around the reference epoch. The nodes with high residual energy take more turns to be the cluster-heads than lower ones.

Coping with heterogeneous nodes

From Eq. (2), we can see that P_{opt} is the reference value of the average probability P_i, which determine the rotating epoch n_i and threshold T (s_i) of node s_i. In homogenous networks, all the nodes are equipped with the same initial energy, thus nodes use the same value P_{opt} to be the reference point of P_i. When the networks are heterogeneous, the reference value of each node should be different

IJDACR International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

according to the initial energy. In the two-level heterogeneous networks, we replace the reference value P_{opt} with the weighted probabilities given in Eq. (6) for normal and advanced nodes [7].

$$P_{adv} = \frac{P_{opt}}{1+am}, \; P_{nrm} = \frac{P_{opt}\,(1+a)}{(1+am)} \qquad 6$$

Therefore, P_i is change into

$$P_i = \begin{cases} \dfrac{P_{opt}\, E_i(r)}{(1+am)\bar{E}\,(r)} & if\ s_i\ is\ the\ normal\ node \\ \dfrac{P_{opt}\,(1+a)E_i(r)}{(1+am)\bar{E}\,(r)} & if\ s_i\ is\ the\ advanced\ node \end{cases} \qquad 7$$

Substituting Eq. (7) for pi on (4), we can get the probability threshold used to elect the cluster-heads. Thus the threshold is correlated with the initial energy and residual energy of each node directly. This model can be easily extended to multi-level heterogeneous networks. We use the weighted probability shown in Eq. (8)

$$P(s_i) = \frac{P_{opt}\, N(1+a_i)}{(N+\sum_{i=1}^{N} a_i)} \qquad 8$$

To replace P_{opt} of Eq. (2) and obtain the P_i for heterogeneous nodes as

$$P_i = \frac{P_{opt}\, N(1+a)E_i(r)}{(N+\sum_{i=1}^{N} a_i)\bar{E}\,(r)} \qquad 9$$

From Eq. (7) and (9), the average energy E(r) is needed to compute the average probability pi. It is difficult to realize such scheme, which presumes that each node knows the average energy of the network. We will estimate E(r) in this paragraph. As shown in Eq. (2) and (5), the average energy E(r) is just used to be the reference energy for each node. It is the ideal energy that each node should own in current round to keep the network alive to the greatest extent. In such ideal situation, the energy of the network and nodes are uniformly distributed, and all the nodes die at the same time. Thus we can estimate the average energy E(r) of r^{th} round as follow:

$$\bar{E}\,(r) = \frac{1}{N} E_{total}\left(1 - \frac{r}{R}\right) \qquad 10$$

Where R denote the total rounds of the network lifetime. It means that every node consumes the same amount of energy in each round, which is also the target that energy-efficient algorithms should try to achieve. From Eq. (5), considering E(r) as the standard energy, DEEC controls the rotating epoch n_i of each node according to its current energy, thus controls the energy expenditure of each round.

As a result, the actual energy of each node will fluctuate around the reference energy E(r). Therefore, DEEC guarantees that all the nodes die at almost the same time. In fact, it is the main idea of DEEC to control the energy expenditure of nodes by means of adaptive approach. To compute E(r) by Eq. (10), the network lifetime R is needed, which is also the value in an ideal state. Assuming that all the nodes die at the same time, R is the total of rounds from the network begins to the entire nodes die. Let Eround denote the energy consumed by the network in each round. R can be approximated as follow

$$R = \frac{E_{total}}{E_{round}} \qquad 10$$

In the analysis, we use the same energy model as proposed in [8]. In the process of transmitting an l-bit message over a distance d, the energy expended by the radio is given by:

$$E_{Tx}(l,d) = \begin{cases} lE_{dec} + l\varepsilon_{fx} d^2, d < d_0 \\ lE_{dec} + l\varepsilon_{mp} d^4, d \geq d_0 \end{cases} \qquad 12$$

Where Eelec is the energy dissipated per bit to run the transmitter or the receiver circuit, and efsd2 or empd4 is the amplifier energy that depends on the transmitter amplifier model. We assume that the N nodes are distributed uniformly in an M *M region and the base station is located in the center of the field for simplicity. Each non-cluster-head send L bits data to the cluster-head a round. Thus the total energy dissipated in the network during a round is equal to:

$$E_{round} = L\left(2NE_{dec} + NE_{DA} + k\varepsilon_{mp} d_{toBS}^4 + N\varepsilon_{fx} d_{toCH}^2\right) \qquad 13$$

Where k is the number of clusters, EDA is the data aggregation cost expended in the cluster-heads, d_{toBS} is the average distance between the cluster-head and the base station, and d_{toCH} is the average distance between the cluster members and the cluster-head. Assuming that the nodes are uniformly distributed, we can get:

$$d_{toCH} = \frac{M}{\sqrt{2\pi k}} \quad d_{toBS} = 0.765\frac{M}{2} \qquad 14$$

By setting the derivative of E_{round} with respect to k to zero, we have the optimal number of clusters as

$$k_{opt} = \frac{\sqrt{N}}{\sqrt{2\pi}} \sqrt{\frac{\varepsilon_{fx}}{\varepsilon_{mp}}} \frac{M}{d_{toBS}^2} \qquad 15$$

Substituting Eqs. (14) And (15) into Eq. (13), we obtain the energy E_{round} dissipated during a round.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

Thus we can compute the lifetime R by (11).

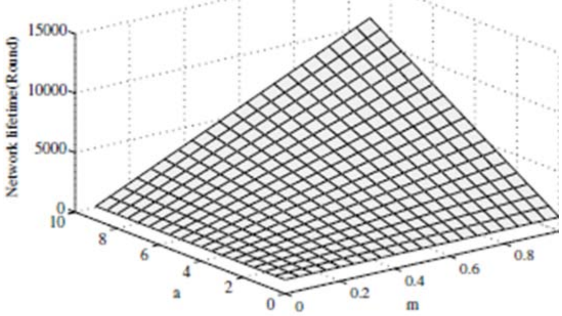

Figure2.Estimate of network lifetime

Initially, all the nodes need to know the total energy and lifetime of the network, which can be determined a priority. In our DEEC protocol, the base station could broadcast the total energy E_{total} and estimate value R of lifetime to all nodes. When a new epoch begins, each node s_i will use this information to compute its average probability pi by Eqs. (10) and (9). Node s_i will substitute pi into Eq. (4), and get the election threshold T (s_i), which is used to decide if node s_i should be a cluster-head in the current round.

II. Methods

Particle swarm optimization (PSO)

The Optimal probability defined in distributed energy efficient clustering protocol is not user defined in our work, we are optimizing it through particle swarm optimization, by simply selecting our protocol as a fitness function for PSO and calculate the optimal value for which our fitness function becomes zero, In the most common implementations of PSO, particles move through the search space using a combination of an attraction to the best solution that they individually have found, and an attraction to the best solution that any particle in their *neighbourhood* has found.

In PSO, a neighbourhood is defined for each individual particle as the subset of particles which it is able to communicate with. The first PSO model used a Euclidian neighbourhood for particle communication, measuring the actual distance between particles to determine which were close enough to be in communication. This was done in imitation of the behaviour of bird flocks, similar to biological models where individual birds are only able to communicate with other individuals in the immediate vicinity. The Euclidian neighbourhood model was abandoned in favour of less computationally intensive models when research focus was shifted from biological modelling to mathematical optimization. Topological neighbourhoods unrelated to the locality of the particle came into use, including what has come to be known as a global neighbourhood, or *gbest* model, where each particle is connected to and able to obtain information from every other particle in the swarm.

Figure4. Birds or fish exhibit such a coordinated collective behaviour

Algorithm

Particle Swarm Algorithm
01. Begin
02. Parameter settings and swarm initialization
03. Evaluation
04. ***g*** = 1
05. While (the stopping criterion is not met) do
06. **for** each particle
07. Update velocity
08. Update position and local best position
09. Evaluation
10. End For
11. Update leader (global best particle)
12. ***g*** + +
15. End While
14. End

The PSO algorithm has several phases consist of Initialization, Evaluation, Update Velocity and Update Position.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

Initialization:
The initialization phase is used to determine the position of the m particles in the first iteration. The random initialization is one of the most popular methods for this job. There is no guarantee that a randomly generated particle is a good answer and this will make the initialization more attractive. A good initialization algorithm makes the optimization algorithm more efficient and reliable. For initialization, some known prior knowledge of the problem can help the algorithm to converge in less iteration.

Update velocity and position:
In iteration each particle updates its velocity and position according to its heretofore best position, its current velocity and some information of its neighbours. Equation 5 is used for updating the velocity.

$$\overline{v_1(t)} = \underbrace{w\overline{v_1(t-1)}}_{inertia} + \underbrace{c_1 r_1\left(x_1^{\#}(t-1) - \overline{x_1(t-1)}\right)}_{personal\ influence} + \underbrace{c_2 r_2\left(x_1^{*}(t-1) - \overline{x_1(t-1)}\right)}_{Social\ influence} \qquad 16$$

Where $\overline{x_1(t)}$ is the position vector in iteration t (i is index of the particle), $\overline{v_1(t)}$ is the velocity vector in iteration t, $x_1^{\#}(t)$ is the best position so far of particle i in iteration t and its j-th dimensional value is $x_{ij}^{\#}(t)$ the best position vector among the swarm heretofore is then in a vector $x_1^{*}(t)$ and its j-th dimensional value is $x_j^{*}(t)$. r1 and r2 are then numbers in interval [0, 1].

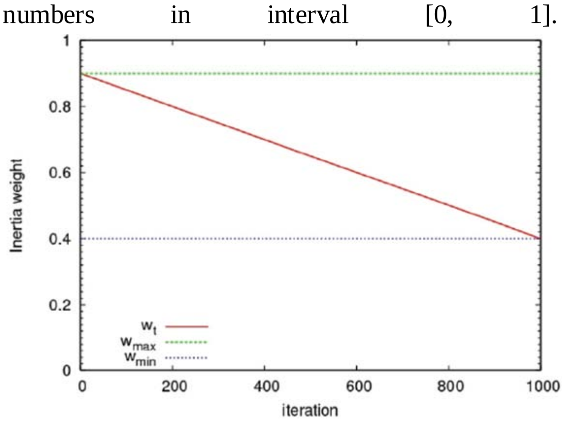

Figure5. The value of the inertia weight is decreased during a run

c1 and c2 is called position constant the variable w is called inertia factor ,which value vary from 0 to 1.

Table1. Parameter settings of the first-order radio model

Parameters	Values
Initial energy (*E0*)	0.5 J/node
Transmitter Electronics (*Eelec*)	50 nJ/bit
Receiver Electronics (*Eelec*)	50 nJ/bit
Data Packet Size (*l*)	2000 bits
Transmitter Amplifier (∑*fs*) if *dδd0*	10 or 100 pJ/bit/m2
Transmitter Amplifier (∑*mp*) if *dεd0*	0.0013 pJ/bit/m4

III. Simulation and Results

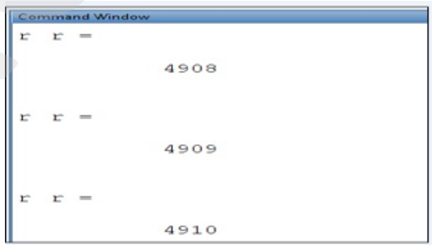

Figure7 round iterations in command window

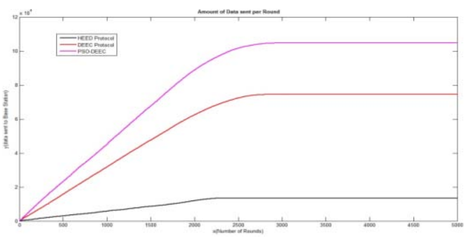

Figure8 amount of data sent respect to rounds

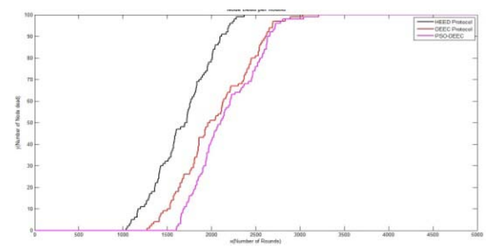

Figure9 Node dead with respect to rounds

IJDACR
ISSN: 2319-4863

International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary research
Website: www.ijdacr.com (Volume 1, Issue 3, October 2012)

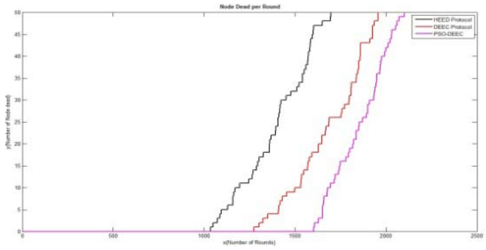

Figure10 Higher stability period of our protocol

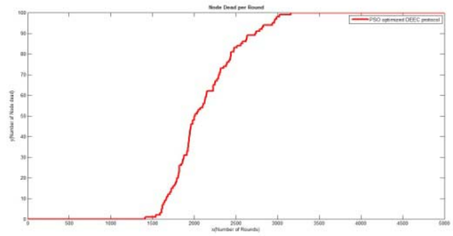

Figure11 standalone graphical view of proposed protocol

Table2.Percentage of Node dead with respect to rounds in our proposed protocol

Percentage of node dead	1%	10%	100%
Round Number	1604	1680	3211

IV. Conclusion

PSO has been a popular technique used to solve optimization problems in WSNs due to its simplicity, high quality of solution, fast convergence and insignificant computational burden. However, iterative nature of PSO can prohibit its use for high-speed real-time applications, especially if optimization needs to be carried out frequently. PSO requires large amounts of memory, which may limit its implementation to resource-rich base stations. Literature has abundant successful WSN applications that exploit advantages of PSO. Data-aggregation needs frequent distributed optimization, and fast solutions: Thus PSO moderately suits it. Static deployment, localization and clustering are the problems solved just once on a base station: Thus PSO highly suits them.

References

[1] Md. Golam Rashed, M. Hasnat Kabir and S. E. Ullah, "WEP: An energy efficient protocol for cluster based heterogeneous wireless sensor network," International Journal of Distributed and Parallel Systems (IJDPS) Vol.2, No.2, March 2011, pp. 54-60.

[2] P. Saini and A. K. Sharma, "Energy Efficient Scheme for Clustering Protocol Prolonging the Lifetime of Heterogeneous Wireless Sensor Networks," International Journal of Computer Applications (0975 – 8887) Vol. 6– No.2, September 2010, pp.30-36.

[3] D. Kumar, T. C. Aseri and R. B. Patel, "Distributed Cluster Head Election (DCHE) Scheme for Improving Lifetime of Heterogeneous Sensor Networks," Tamkang Journal of Science and Engineering, Vol. 13, No. 3, 2010, pp. 337-348.

[4] V. Katiyar, N. Chand, S. Soni, "A Survey on Clustering lgorithms for Heterogeneous Wireless Sensor Networks" Int. J. Advanced Networking and Applications Vol. 02, Issue: 04, pp. 745-754, 2011.

[5] 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.

[6] A. A. Abbasi and M. Younis, "A survey on clustering algorithms for wireless sensor networks," Computer Communications 30, 2007, pp. 2826-2841.

[7] V. Kawadia and P. R. Kumar, "Power Control and Clustering in Ad Hoc Networks," in Proceedings of IEEE INFOCOM, April 2003.

[8] S. Bandyopadhyay, E.J. Coyle, An energy efficient hierarchical clustering algorithm for wireless sensor networks, in: Proceeding of INFOCOM 2003, April 2003.