IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 18, Issue 1, Ver. III (Jan – Feb. 2016), PP 41-49
www.iosrjournals.org

Review of Evolutionary Algorithms in Wsn

Amanjot Kaur[1], Gaurav Mehta [2]
[1,2] *(Department of Computer Science, Chitkara University, India)*

***Abstract**: Diverse issues related to wireless sensor networks like energy minimization (optimization), compression schemes, network algorithms which are self-organizing, routing protocols, management of quality of service, security etc., have been broadly investigated. Among these, energy efficiency, quality of service and management of security are the most indispensable issues. To get the best feasible results in one or more of these issues in wireless sensor networks optimization is vital. In classical algorithms, energy consumption is very high due to random selection of CH (cluster head). Due to high energy consumption and data processing requirements; use of classical algorithms has been disregarded. Contemporary researchers have started using Bio-mimic strategy based optimization techniques [1]. There is no such one algorithm which can take care of all aspects of CH selection. These techniques are diverse and involve many different optimization algorithms. The focal point of the most existing works is optimization of one particular issue of the three mentioned. In this paper we are presenting a review of the literature in the area of wireless sensor network optimization focusing on the four generally used optimization techniques, namely, particle swarm optimization, genetic algorithm, Harmony search algorithm and flower pollination*

***Keywords:** Flower pollination algorithm, Genetic Algorithm**,** Harmony search algorithm and Particle swarm optimization,*

I. Introduction

Wireless sensor network (WSN) is an intellectual solution with low cost that facilitate the boost in efficiency and reliability of many industrial applications such as safety and security surveillance, home and building automation, and smart grids. The WSNs usually comprise of a large number of sensor nodes which are low-power and small in size [1].Sensor nodes acting as autonomous devices can be deployed in various types of environments However; there are many challenges to implement the WSNs into real-life applications. To enlarge their lifetime is one of the key concerns when developing the WSNs. In many applications, a sensor node is provided energy by a finite energy source like a battery or a super capacitor that limits the WSNs' lifetime. The energy sources which are renewable like solar or wind have been examined and fused with the sensor nodes recently to operate for longer duration [2]–[5]. However, the irregular nature of these sources still has a considerable effect on the performance of network. Therefore, energy expenses of the WSNs are taken into account when planning the operation of network. Cluster-based routing protocols are well-known techniques that help in making the operation of WSNs to be highly energy-efficient. Organizing the sensor nodes into groups called clusters is the fundamental principle of a cluster-based protocol. In each cluster, a node is chosen as the cluster head (CH) ,having responsibility to collect data from other cluster members, combine, and forward the compact information to a base station (BS).By using this principle, it is able to lessen the amount of data transferred within the network, thereby saving energy. Many cluster-based protocols have been projected with the objective to maximize the network lifetime in the literature such as energy-aware routing ,TEEN,APTEEN, PEGASIS, low-energy adaptive clustering hierarchy(LEACH), and Fuzzy C-Means (FCM) [7]–[15]. However, most of these protocols are studied by using simulation tools. Models of the networks used are approximated; hence the investigated performance may not represent the exact behavior of the systems in practice.

A typical cluster-based protocol such as LEACH which along with working in a distributed manner, selects CHs based on a predetermined probability in order to enable the rotation if the CH role among the sensor nodes and avoid fast depletion of the CH's energy[12]. As most of the cluster-based protocols, the two phases in the operation of LEACH are: *setup phase* and *data transmission phase*. The formation of the clusters is carried out in setup phase. Information acquired by sensor nodes is transferred to the BS in the data transmission phase. Simulation-based study of LEACH takes into account only energy consumption for receiving the advertisements from CHs at each sensor node during the setup phase. However, since nodes elect themselves to the CH arbitrarily, the exact moment at which the advertisement message from the CH is transmitted is unknown for the other nodes. Therefore, more energy is consumed in practice as nodes must keep listening for these messages. Furthermore, it is stated that the operation of LEACH is divided into rounds, but nothing about synchronization of nodes to follow this scheme is discussed. LEACH-centralized (LEACH-C) is an improvement of LEACH, which uses a centralized clustering mechanism to form the clusters [13]. LEACH-C produces better clusters by dispersing the CHs throughout the network, thereby enhances the network performance. A fuzzy-logic-based clustering approach with an energy-prediction mechanism for LEACH during the CH selection to further augment the network lifetime has been proposed [14] . However, all of these protocols are inspected through simulation studies; an approximated radio energy model described in [12] and [13] is required to evaluate network performance. The classical clustering methods may not succeed in finding the optimum solution of the problem and often get trapped in local minima, since these methods are extremely sensitive to starting points and often converge to a local optima or deviate altogether [16]–[18]. Metaheuristic algorithms, such as, evolutionary programming, genetic programming genetic algorithms (GA), HSA, ant colony optimization, particle swarm optimization (PSO), differential evolution and Bee algorithm, eliminate some of the aforementioned difficulties and are quickly taking place of the classical methods [1].

II. Related Work

Many clustering and routing algorithms have evolved for WSNs. A review of such works based on heuristic and metaheuristic approaches is presented.

2.1. Heuristic Approaches

A clustering algorithm to find out the least loaded gateway for assigning a sensor node to CH by considering a breadth-first search (BFS) tree of the sensor nodes has been presented in [25]. The time required for execution of this algorithm is very high for a large scale WSN as for n sensor nodes and m CHs, the algorithm has the time complexity of O (mn^2). A substantial amount of memory space is needed for building a BFS tree for individual sensor node in this algorithm. For an improvement over an algo of [1], a load balanced clustering algorithm that runs in O (n log n) is proposed by Kuila and Jana in [26]. LBC , a clustering algorithm have been proposed by Gupta and Younis in [27] ,which takes O(mn log n) time in worst case. EELBCA, an energy efficient load-balanced clustering algorithm with O(n log m) time has been put forward by Kuila and Jana in [28]. EELBCA, a min-heap based clustering algorithm, addresses energy efficiency as well as load balancing. Building of min-heap involves usage of cluster heads (CHs) on the number of sensor nodes allotted to the CHs. However, residual energy of the sensor nodes is not taken into account in these algorithms Many heuristics have also been proposed for routing in WSNs. A popular cluster-based routing algorithm that comprises of dynamic rotation of the load of the CHs amongst the sensor nodes which is useful for load balancing is LEACH in [29].However, selection of a node as CH with very low energy is the main disadvantage of this approach as it may die quickly. Moreover, communication of CHs with base station via single-hop is impractical for WSNs with large coverage area due to which a variety of algorithms have been brought into light to improve LEACH which can be found in [30]-[31]. For selection of CH and formation of clusters, a cost based distributed energy balanced clustering and routing algorithm has been proposed by Kuila and Jana in [32] but, the algorithm suffers from the connectivity problem of the selected CHs.

2.2. Metaheuristic Approaches

Most of the metaheuristic based clustering algorithms that have been reported for WSNs dealt with CH selection only. Recently, a GA-based load balanced clustering algorithm put forward by (Kuila et al.[33]) for WSNs in which the formation of clusters takes place in such a manner that there is minimization of the maximum load of each gateway .This algorithm is valid for both the equal and unequal load of the sensor nodes. In comparison to traditional GA(Goldberg, [34]), this algorithm has faster convergence and better load balancing .However, the direct communication of CHs with the BS which may not be practical for large area networks is demerit of this algorithm. There is no consideration regarding residual energy of the sensor nodes and gateways in cluster formation which may direct to inequity in energy consumption of the sensor nodes in this algorithm. A GA-based algorithm has been proposed in [35] for routing of data between gateways in a two-tire wireless sensor network. Roulette-wheel selection method is used to accomplish the task of selection of individuals and the fitness function is defined by network lifetime in terms of rounds. The overall communication distance from the gateways to the BS is minimized in (Gupta et al., [33]). However, both of the algorithms (Ataul et al., 2009[35]; Gupta et al., [33]) take into account only aggregated data's routing from the gateways to the BS without paying heed to data communication from the sensor nodes to the gateways within each cluster. For clustering of wireless sensor networks dynamically, an evolutionary aware routing protocol (EAERP is presented in [36]. In this minimization of energy utilization all over the network has been attempted by selecting a set of efficient cluster heads from the normal sensor nodes and CH nearest to join is determined by all non-CH sensor nodes. EAERP suffers identical problem as LEACH, as some sensor node having insufficient energy may become a CH. Furthermore, re-clustering is vital in EAERP in each round for change of the extra work load of CH at regular intervals. Unfortunately, as EAERP is a centralized approach; in each round for re-clustering the whole network information is essential. A routing algorithm based on differential evolution for more than a 1000 relay nodes is presented in [37] to minimize the energy consumption of the relay node with maximum energy-consumption, but the cluster formation is not taken into consideration. Serious energy inefficiency of the relay nodes can result from improper clustering PSO has been used for CH selection amongst the normal sensor nodes and cluster formation is not taken care of [38]-[39] . PSO and ant colony optimization (ACO) are applied in WSNs for other optimization problems also and they can be found in [40]-[42]. However, the overhead of data routing in phase of cluster formation is not considered in any of the above algorithms. Even, nature inspired approach with focus on cluster formation has not been used with any of the above algorithms except Kuila [43].

III. Four Evolutionary Algorithms

3.1. Genetic Algorithm

A. Overview

A genetic algorithm (GA) [20] is a search technique used in engineering to find estimated solutions to optimization and search problems. Genetic algorithms are a specific class of evolutionary algorithms that use techniques inspired by nature such as inheritance, mutation, selection, and crossover (also called recombination). Size of Population, rate of crossover, number of generations and mutation rate are the main parameters used in the GA strategy.

B. Details About The Algorithm

(A) Initialization

Initially, there is Random generation of many individual solutions to create an initial population which covers the entire collection of potential solutions (the search space).

(B) Selection

During each consecutive epoch, a percentage of the substantial population is chosen to breed a new generation. Selection of Individual solutions is through a fitness-based process like roulette wheel selection, where fitter solutions are typically more expected to be selected.

(C) Reproduction

The following step is to generate a second generation population of solutions from those chosen through genetic operators: crossover (also called recombination), and mutation. A pair of "parent" solutions is specified for breeding from the pool selected previously for each new solution to be formed. Selection of new set of parents is done each time and the process remains persistent until a new population of solutions of suitable dimensions is generated.

(D)Termination

Repetition of this generational process is done until we reach the termination condition .Here the fixed number of generations reached is taken as the procedure for the termination of the program.

C. Pseudo-Code

- Choose initial population
- Repeat
- Evaluate the individual fitness of a certain fraction of the population
- Select pairs of best-ranking individuals to reproduce
- Raise new generation through crossover and Mutation
- Continue until terminating condition

3.2. Particle Swarm Optimization Algorithm

A. Overview

PSO was developed by Kennedy and Eberhart. The PSO is inspired by the social behavior of a flock of migrating birds trying to reach an unknown destination [21]. In PSO, each solution is a ‘bird’ in the flock and is referred to as a ‘particle’. A particle is similar to a chromosome (population member) in GAs. As opposed to GAs, in the evolutionary process in the PSO there is no creation of new birds from parent ones. Rather, the birds in the population only change their social behavior and accordingly their movement towards a destination.

B. Details About The Algorithm

(A) Initialization

The process is initialized with a set of arbitrary particles (solutions), N. To represent the i^{th} particle we use its position as a point in an D-dimensional space. Each particle i monitors three values throughout the process which are : its current position (Xi); the best position it reached in previous cycles($pbest_i$); its flying velocity (V_i) .

(B)Swarming

In each time interval (cycle), the position of the best particle (gbest) is calculated as the best fitness of all particles. Accordingly, each particle updates its velocity Vi to get closer to the best particle gbest, as follows :$V_i^{k+1}=w.V_i^k+C_1.rand_1.(pbest_i^k-x_i^k)+C_2.rand_2.(gbest_i^k-x_i^k)$……(1) Where w is the weight factor for that iteration; given by:

$w=w_{max}-(w_{max}-w_{min})/iteration_{max}.\ iteration$……….. (2)

Also, C1 and C2 are two positive constants named learning factors; rand1 and rand2 are two random functions in the range [0, 1]. As such, using the new velocity Vi, the particle's updated position becomes: $X_i^{k+1}=X_i^k+V_i^{k+1}$ ………(3)

As such, the main parameters used in the PSO technique are: the population size (number of particles), number of generations and the weight factor w. Swarming is done till the termination condition is attained.

C. Pseudo-Code

- Generate a random population of N solutions or particles
- Repeat
- For each particle, calculate fitness
- Initialize the value of the weight factor(w) for that iteration
- For each particle, set pbest as the best position of that particle.
- Set gbest as the best fitness of all particles.
- For each particle, calculate particle velocity (V).
- Update particle position (X)
- Continue until terminating condition

3.3 Harmony Search Algorithm

A. Overview

The musical process of finding for a perfect condition of harmony [22] encourages the HSA by seeking a perfect state of harmony evaluated by aesthetic estimation, as the best state (i.e., global optimum) decided by objective function value is searched by optimization algorithm.

B. Details About The Algorithm

(A) Initialization

In the formulated problem, in order to decrease the intra-cluster distances and optimize the energy consumption of the network, which is defined by the objective function, HSA is applied. In the solution vector what we get is the identification (ID) of the CHs among the candidates in the network. *Harmony Memory Size (HMS)*, the number of solutions vector in Harmony Memory Matrix, is selected. It has similarity to population in GA. *Harmony Memory Considering Rate (HMCR)* and *Pitch Adjusting Rate (PAR) is the* other parameters used to create new solution vector which are initiated. The maximum iteration of executing the algorithm (stopping criterion) is also set. Random generation of an HM consisting of an *HMS* number of solution vectors for the formulated problem is done. Each row of the HM is a random solution vector containing elements. These elements are the IDs of k different CHs selected from the set of candidates[19].

(B) Updation Of HM

After defining the HM, the improvisation of the HM is carried out by generating a new harmony vector. Evaluation of the newly generated harmony vector is done in terms of the objective function value. If the objective function value for the new Harmony vector is better than the objective function value for the worst harmony in the HM, then new Harmony is incorporated in the HM and the existing worst harmony is disqualified from the HM. The optimal solution of the problem in the current iteration can be considered as the solution vector with the smallest fitness value[19].

(C)Termination

The current best solution is selected from the HM after the termination criterion is satisfied. This is the solution for the optimization problem formulated [19].

C. Pseudo-Code

- Initialize the optimization problem and algorithm parameters.
- Initialize the harmony memory (HM).
- Improvise a new harmony from the HM.
- Update the HM.
- Go to step 3 until termination criterion is reached.

3.4 Flower Pollination Algorithm

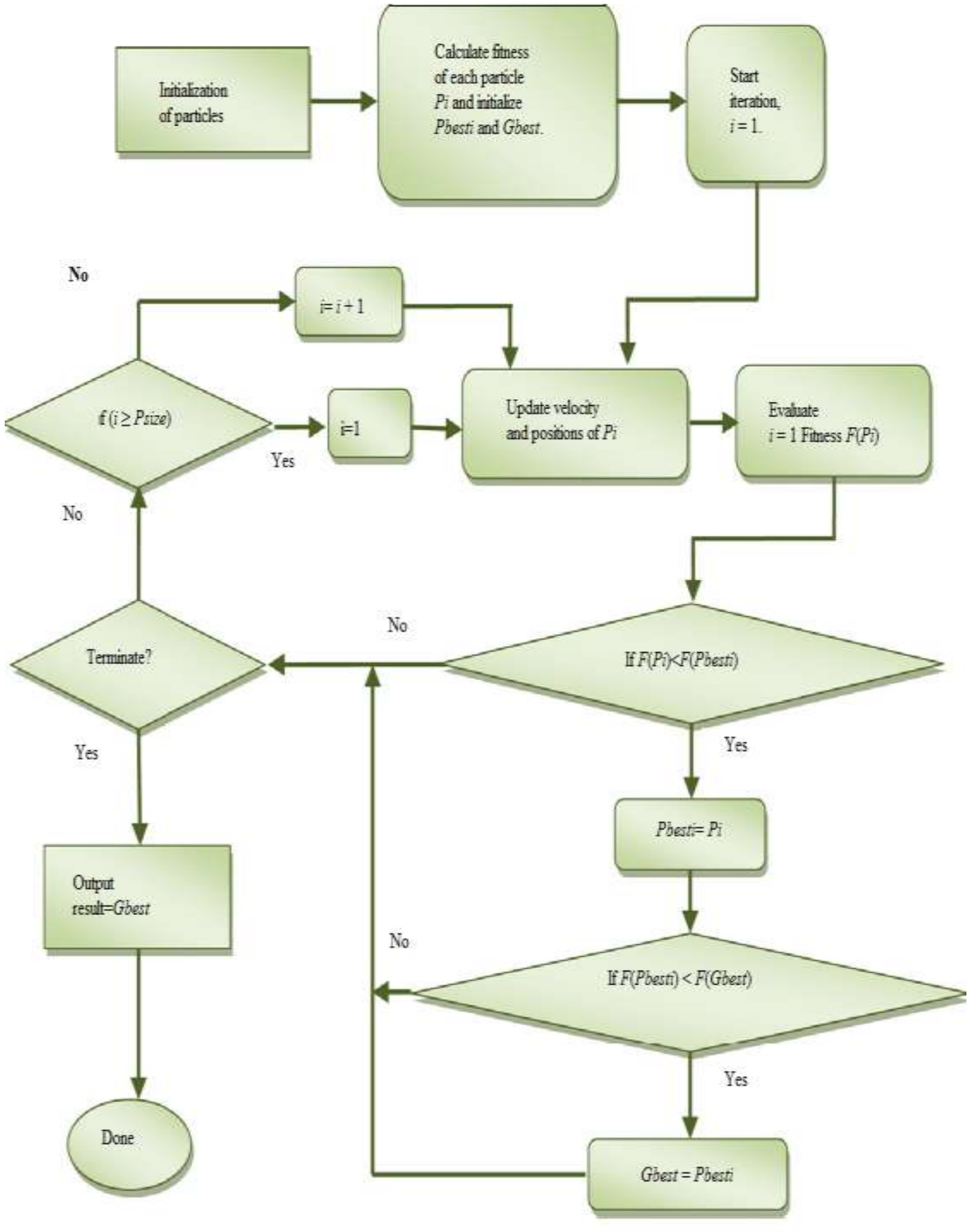
A. Overview

Xin-She Yang developed the Flower pollination algorithm(FPA) in 2012 [23]. For simplicity, we use the following four rules:

1. Biotic and cross-pollination can be considered as a process of global pollination process, and pollen-carrying pollinators move in a way which obeys L´evy flights (Rule 1).
2. For local pollination, abiotic and self-pollination are used (Rule 2).
3. Pollinators such as insects can develop flower constancy, which is equivalent to a reproduction probability that is proportional to the similarity of two flowers involved (Rule 3).
4. The interaction or switching of local pollination and global pollination can be controlled by a switch probability $p \in [0, 1]$, with a slight bias towards local pollination (Rule 4).

B. Details About The Algorithm And Pseudo-Code[24]

- *Objective function min or* max f(x), $x=(x_1, x_2, x_3,\ldots, x_d)$
- *Initialize* a population of *(n)* flowers/pollen gametes with random solutions
- *Find the best solution* g_k in the initial population
- *Define a switch probability* $p \in [0, 1]$
- *Define stopping criteria* (either a fixed number of generations/ iterations or accuracy)
- While *(t <MaxGeneration)*
- For i = 1: n *(all n flowers in the population)*
- If *rand* < *p,*
- *Draw a (d-dimensional) step vector L which obeys L'evy's distribution*
- *Global pollination via* $x_i^{t+1} = x_i^t + L(x_i^t - g_k)$
- *Draw from a uniform distribution in [0, 1]*
- *Randomly choose j and k among all the solutions*
- *Do local pollination via* $x_i^{t+1} = x_i^t + E(x_j^t - x_k^t)$
- End if
- *Evaluate new solutions*
- If *new solutions are better, update them in the population*
- End For
- *Find the current best solution* g_k
- End While
- *Output the best solution found*
- End



FLOWCHART OF PSO[6]

Category	Representative Protocols	Description
Location-based Protocols	MECN, SMECN, GAF, GEAR, Span, TBF, BVGF, GeRaF	Requirement of information regarding sensor nodes to calculate the distance between two particular nodes so that energy consumption can be estimated.
Data-centric Protocols	SPIN, Directed Diffusion, Rumor Routing, COUGAR, ACQUIRE, EAD, Information-Directed Routing, Gradient-Based Routing, Energy-aware Routing, Information-Directed Routing, Quorum-Based Information Dissemination, Home Agent Based Information Dissemination	Data is sent from source sensors to the sink. When data is being transmitted by source nodes to the sink, some aggregation is performed on data originating from multiple source sensors and that aggregated data is sent toward the sink
Hierarchical Protocols	LEACH, PEGASIS, HEED, TEEN, APTEEN	A network is composed of several *clumps* (or *clusters)* of sensors. Each clump is managed by a special node, called *cluster head*, which is responsible for coordinating the data transmission activities of all sensors in its clump.
Mobility-based Protocols	SEAD, TTDD, Joint Mobility and Routing, Data MULES, Dynamic Proxy Tree-Base Data Dissemination	Sink mobility requires energy efficient protocols to guarantee data delivery originated from source sensors toward mobile sinks.
Multipath-based Protocols	Sensor-Disjoint Multipath, Braided Multipath, N-to-1 Multipath Discovery	There are two routing paradigms: *single-path* routing and *multipath* routing. In single-path routing, each source sensor sends its data to the sink via the shortest path. In multipath routing, each source sensor finds the first k shortest paths to the sink and divides its load evenly among these paths.
Heterogeneity-based Protocols	IDSQ, CADR, CHR	There are two types of sensors namely line-powered sensors which have no energy constraint, and the battery-powered sensors having limited lifetime, and hence should use their available energy efficiently by minimizing their potential of data communication and computation.
QoS-based protocols	SAR, SPEED, Energy-aware routing	Consideration of quality of service (QoS) requirements in terms of delay, reliability, and fault tolerance in routing in WSNs

Table 3.1 Different categories of Routing Protocols in Wireless Sensor Network

Different Optimization Techniques used in Wireless sensor networks for optimizing energy requirements are compared in following section.

Criteria	Genetic	PSO	FPO	HSA
Methods	Survival of fittest	Position and velocity of particle	Optimize formation of clusters; optimally associates clusters' nodes to each cluster based on intracluster distances optimization fitness function	Harmony matrix creation and updation. Distance between CH and Cluster member is reduced.
Performance	Used in formation of number of predefined clusters which helped in reducing overall mi-nimum communicat-ion distance	Better in selecting high energy node as CHs in each round and can find optimal route effectively	Selects best CH's distribution that guarantees a routing optimization with minimum communication cost between nodes within each cluster.	Used for safety and surveillance applications; to monitor ambient temperature for fire detection.
Parameters	Size of Population, rate of crossover, number of generations and mutation rate	The population size (number of particles), number of generations and the weight factor w	Standard gamma, local random walk, switch probability	HMS harmony memory size, H M(Harmony Matrix) ,HMCR,PAR

Table 3.2 Comparison Of Optimization Techniques In Wireless Sensor Network

IV. Conclusions

From various studies on routing protocols ,we have realised that as maximum energy is consumed in Cluster formation phase ,nothing can be done only with the utiliza tion of routing protocols in Wireless Sensor networks .We need to use optimization techniques based on the nature in order to achieve minimization of energy consumption.In this paper,various optimization techniques are compared on the basis of existing studies on them.Future scope includes applying routing protocol in combination with any of the optimization techniques in order to make efficient cluster formation.

References

[1] M.A.Adnan, M.A.Razzaque, I.Ahmed and I.F.Isnin, Bio-Mimic Optimization Strategies in Wireless Sensor Networks: A Survey, Sensors 2014, 14, 2014, 299-345.

[2] Y. K. Tan and S. K. Panda, Energy harvesting from hybrid indoor ambient light and thermal energy sources for enhanced performance of wireless sensor nodes, IEEE Trans. Ind. Electron., 58(9), Sep. 2011, 4424-4435.

[3] Y. K. Tan and S. K. Panda, Self-autonomous wireless sensor nodes with wind energy harvesting for remote sensing of wind-driven wildfire spread, IEEE Trans. Instrum. Meas., 60(4), 1367–1377.

[4] Y. K. Tan and S. K. Panda, Optimized wind energy harvesting system using resistance emulator and active rectifier for wireless sensor nodes, IEEE Trans. Power Electron., 26(1), Jan. 2011, 38–50

[5] B. Zhang, R. Simon, and H. Aydin, Harvesting-aware energy management for time-critical wireless sensor networks with joint voltage and modulation scaling, IEEE Trans. Ind. Inf., 9(1), Feb. 2013, 514–526

[6] P. Kuila, P.K. Jana, Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach, Engineering Applications of Artificial Intelligence, 33, August 2014, 127-140.

[7] M. Younis, M. Youssef, and K. Arisha, Energy-aware routing in cluster-based sensor networks, in Proc. 10th IEEE/ACM Int. Symp. Modeling, Anal. Simulation Comput. Telecommun. Syst., Fort Worth, TX, USA, Oct. 2002, 129–136.

[8] A.Manjeshwar and D. P. Agrawal, Teen: a protocol for enhanced efficiency in wireless sensor networks, in Proc. 1st Int.Workshop Parallel Distrib. Comput. Issues Wireless Netw. Mobile Comput, San Francisco, CA, USA, Apr. 2001, 2009–2015.

[9] A. Manjeshwar and D. P. Agrawal, Apteen: a hybrid protocol for efficient routing and comprehensive information retrieval in wireless sensor networks, in Proc. 2nd Int.Workshop ParallelDistrib. Comput. Issues in Wireless Netw. Mobile Comput, Ft. Lauderdale, FL, USA, Apr. 2002, 8–15.

[10] S. Lindsey and C. S. Raghavendra, Pegasis: power efficient gathering in sensor information systems, in Proc. IEEE Aerospace Conf., Big Sky,MT, USA, Mar. 2002, 1125–1130.

[11] S. D. Muruganathan, C. F. Daniel, R. I. Bhasin, and A. O. Fapojuwo, A centralized energy-efficient routing protocol forwireless sensor networks, IEEE Commun. Mag., 43(3), Mar. 2005, 8–13.

[12] W. Heinzelman, A. Chandrakasan, and H. Balakrishnan, Energy-efficient communication protocols for wireless microsensor networks, in Proc. 33rd Annu. Hawaii Int. Conf. Syst. Sci., Jan. 2000, 1–10.

[13] W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan, An application- specific protocol architecture for wireless microsensor networks, IEEE Trans. Wireless Commun., 1, 2002, 660–670

[14] J. S. Lee and W. L. Chen, Fuzzy-logic-based clustering approach for wireless sensor networks using energy predication, IEEE Sensors J., 12(9), Sep. 2012, 2891–2897

[15] D. C. Hoang, R. Kumar, and S. K. Panda, Fuzzy C-means clustering protocol for wireless sensor networks, in Proc. IEEE Int. Symp. Ind.Electron., 2010, 3477–3482.

[16] P. Yadav, R. Kumar, S. K. Panda, and C. S. Chang, Improved harmony search algorithm based optimal design of the brushless DC wheel motor, in Proc. IEEE Int. Conf. Sustainable Energy Technol., Kandy, Srilanka, 2010, 1-5.

[17] P. Yadav, R. Kumar, S. K. Panda, and C. S. Chang, An improved harmony search algorithm for optimal scheduling of the diesel generators in oil rig platforms, Energy Conv.Manag., 52(2) , Feb. 2011, 893–902.

[18] P .Yadav, R. Kumar, S. K. Panda, and C. S. Chang, Energy-efficient thrust allocation for semi-submersible oil rig platforms using improved harmony search algorithm, IEEE Trans. Ind. Inf., 8(4), Nov 2012, 913-924.

[19] D.C. Hoang,P. Yadav,R. Kumar, and S.K. Panda, Real Time Implementation of a Harmony Search Algorithm based Clustering Protocol for Energy Efficient Wireless Sensor Networks, IEEE transactions on industrial informatics, 10, February 2014, 774-783

[20] Ioannis G. Damousis, Anastasios G. Bakirtzis, and Petros S.Dokopoulos, Network-Constrained Economic Dispatch Using Real-Coded Genetic Algorithm, IEEE Trans. On Power Systems, 18(1), February 2003, 198-205.

[21] A. Immanuel Selvakumar and K. Thanushkodi , A new particle swarm optimization Solution to nonconvex economic dispatch problems, IEEE Trans. on power systems, 22(1), Feb 2007, 42-51

[22] Z. W. Geem, J. H. Kim, and G. V. Loganathan, A new heuristic optimization algorithm: harmony search, Simulation, 76(2), 2001,60-68.

[23] Yang, X. S., Flower pollination algorithm for global optimization, in: Unconventional Computation and Natural Computation Lecture Notes in Computer Science, 7445, 240-249

[24] Xin-She Yanga, Mehmet Karamanoglua, Xingshi He, Multi-objective Flower Algorithm for Optimization, International Conference on Computational Science, ICCS 2013, Procedia Computer Science 18 (2013) ,861 – 868

[25] Low, C.P., et al., Efficient load-balanced clustering algorithms for wireless sensor networks, Comput. Commun. 31, 2008,750–759.

[26] Kuila, P., Jana, P.K., Approximation schemes for load balanced clustering in wireless sensor networks, J. Supercomput. 68, 2014,87–105

[27] Gupta, G., Younis, M., Load-balanced clustering of wireless sensor networks. In: IEEE ICC 2003, 1848–1852.

[28] Kuila, P., Jana, P.K., 2012b. Energy efficient load-balanced clustering algorithm for wireless sensor network. In: ICCCS 2012, Procedia Technology ,6, 771–777.

[29] Heinzelman, W.B., Application specific protocol architecture for wireless microsensor networks. IEEE Trans. Wirel. Commun. 1, 2002, 660–670.

[30] Tyagi, S., Kumar, N, A systematic review on clustering and routing techniques based upon LEACH protocol for wireless sensor networks, J .Netw. Comput Appl. 36, 2013, 623-645.

[31] Al-Refai, H, .Efficient routing LEACH (ER-LEACH) enhanced on LEACH protocol in wireless sensor networks. Int. J. Acad. Res. (Part I) 3, 2011, 42–48.

[32] Kuila, P., Jana, P.K., c. An energy balanced distributed clustering and routing algorithm for wireless sensor networks .In: PDGC 2012, IEEE Xplore, 220-225.

[33] Gupta, S.K., Kuila, P., Jana, P.K, GAR: an energy efficient GA-based routing for wireless sensor networks, In: ICDCIT 2013, LNCS 7753, 2013, 267–277.

[34] Goldberg, D.E., Genetic Algorithms: Search Optimization and MachineLearning. Addison Wesley, Massachusetts,2007

[35] Ataul, B., et al., 2009. A genetic algorithm based approach for energy efficient routing in two –tiered sensor networks. Ad Hoc Netw, 655-676.

[36] Enan, A., 2011. Energy-aware evolutionary routing protocol for dynamic clustering of wireless sensor networks. Swarm Evol. Comput, 1,195-203.

[37] Chakraborty, U.K., Energy-efficient routing in hierarchical wireless sensor networks using differential-evolution-based memetic algorithm. In: IEEE WCCI , 2012, 1-8.

[38] Singh, B., Lobiyal, D.K., 2012. Energy-aware cluster head selection using particle swarm optimization and analysis of packet retransmission in WSN. Procedia Technol.4, 2012, 171-176.

[39] Abdul, L.N.M., Energy aware clustering for wireless sensor networks using particle swarm optimization ,In: IEEE PIMRC,2007,1-5.

[40] Saleem, M., et al.. Swarm intelligence based routing protocol for wireless sensor networks: survey and future directions. Inf. Sci, 181, 2011, 4597-4624.

[41] Kulkarni, R.V.,Particle swarm optimization in wireless-sensor networks: a brief survey. IEEE Trans. Syst., Man, Cybern.–Part C: Appl. Rev. 41, 2011, 262-267.

[42] Zungeru, A.M., Classical and swarm intelligence based routing protocols for wireless sensor networks: a survey and comparison. J. Netw. Comput. Appl, 35, 2012, 1508–1536.

[43] Kuila, P., Gupta, S.K., Jana, P.K,A novel evolutionary approach for load balanced clustering problem for wireless sensor networks”, Swarm Evol. Comput. 12, 2013, 48–56