International Journal of Pure and Applied Mathematics
Volume 101 No. 5 2015, 773-807
ISSN: 1311-8080 (printed version); ISSN: 1314-3395 (on-line version)
url: http://www.ijpam.eu

SWARM INTELLIGENCE IN WIRELESS SENSOR NETWORKS: A SURVEY

M. Vergin Raja Sarobin[1], R. Ganesan[2]
[1,2]School of Computing Science and Engineering
VIT University
Chennai, INDIA

Abstract: The recent advances in Wireless Sensor Network (WSN) have gained world-wide attention because of its minimized size, low cost and untethered nature. These sensor nodes has sensing unit to collect the data from physical environment, processing unit to process the data and communicating component to communicate sensory data to base station over wireless medium. WSN placement is very specific to applications such as environment monitoring, habitat monitoring, military applications, health monitoring, object tracking and smart grids. In most of these applications numerous sensors nodes are remotely deployed and they are set to operate autonomously. WSN designers face many issues that arise due to limited battery, harsh environment, communication failures, memory and bandwidth. Among this, limited power source is the primary issue that needs high priority attention. However, the open challenges

Received: March 12, 2015

in WSN such as network lifetime, connectivity, coverage are all proved as NP complete problems. For this reason several swarm intelligence (SI) techniques have been used to address WSN issues to bring efficient optimization solution. Compared to other communication and topology control protocol, the usage of SI techniques is very minimal among WSN researchers. This depicts that the WSN designers and developers are not fully aware of SI techniques. On the other hand soft computing experts are not completely aware of the WSN issues and the possibility of exploiting SI algorithms in WSN. This survey summaries the research challenges in WSN, introduces several SI techniques and tries to bridge the gap between WSN and SI researchers. It also describes the application of SI in WSN design and deployment, clustering, scheduling, localization, data aggregation and QoS Management.

Key Words: wireless sensor networks, swarm intelligence, clustering, design and deployment, scheduling, localization, data aggregation, quality of service, energy efficiency, network lifetime

1. Introduction

Wireless Sensor Network (WSN) consists of spatially distributed low-cost sensor nodes which collect the data within the sensing range and transmit them to the Base Station (BS) or sink as shown in Figure 1. The BS either accepts the data locally or through the gateway of other networks (see [1]). The data collected will be related to environmental conditions, such as temperature, sound, vibration, pressure, motion etc. The literature survey shows the necessity of WSN in various applications like: structural health monitoring (see [2], [7]), wild life monitoring, modern power system (see [3], [4]), smart home (see [5]), smart car parking (see [6]), weather monitoring, military etc. The sensor nodes in WSN are small battery powered devices with limited energy source. After deploying the sensor nodes in their sensing field it is very difficult for the user to replace the energy source. Basically, sensor network lifetime can be extended by reducing energy consumption (see [1]). Thereby the cost of the network will become cheaper.

The ideal wireless sensor network should be scalable, energy efficient, smart and software programmable, reliable and accurate over the long term, low cost to purchase and install, and requires low maintenance. In general sensor nodes are randomly deployed. For the betterment of reliability, connectivity and network coverage, the number of sensor nodes are extensively increased (see [1]).

The open challenges in WSN such as network lifetime, node deployment, connectivity, coverage, node scheduling, localization, node clustering, data gathering are all proved as NP complete problems. Energy consumption is very crucial among other issues in WSN (see [8]). Energy consumption and long-distance transmission will go hand-in-hand. Power required for long distance transmission is high. The prominent method to reduce the distance of data transmission among the nodes is clustering (see [9]) thereby the energy efficiency and network lifetime can be improved. The sensor nodes in the whole sensing terrain are divided into several clusters with one node as Cluster Head (CH) in each cluster. The remaining nodes are Cluster Member (CM). It is the responsibility of the CH to collect all the sensed data from its CMs and send it to the BS directly or via other CHs. Apart from energy aware clustering, energy efficiency of WSN can also be improved through energy aware design and deployment, energy aware node scheduling, energy aware routing, energy aware data gathering etc.

Conventional analytical computation techniques require vast computational efforts that grow exponentially proportional to problem size. Optimization techniques provoked by bio-inspired natural phenomena is considered as an alternative for analytical methods. Swarm intelligence (SI) is one such optimization technique (see [16]). Almost all the SI techniques evolved so far, are from the natural biological systems such as termites colonies (see [18]), swarm of bees (see [23]), swarm of birds (see [24]) etc. Compared to other communication and topology control protocol, the usage of SI techniques is very minimal among WSN researchers. This depicts that the WSN designers and developers are not fully aware of SI techniques. On the other hand soft computing experts are not completely aware of the WSN issues and the possibility of exploiting SI algorithms in WSN. This survey paper summaries the research challenges in WSN, introduces several SI techniques and tries to bridge the gap between WSN and SI researchers. The paper also describes the application of SI in WSN design and deployment, clustering, scheduling, localization, data aggregation and QoS management.

The rest of the paper is organized as follows: Major issues of WSN are highlighted in Section 2. Swarm Intelligence and its relative advantages are briefly outlined in Section 3. Section 4-7 discusses applications of Swarm Intelligence in efficient deployment, scheduling, clustering and data aggregation. At last, a summary of future research trends in applying SI methods in WSN is presented in section 6.

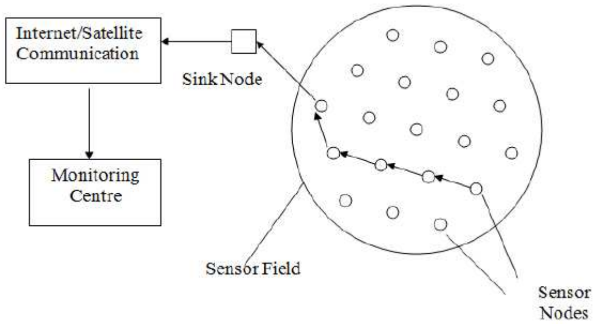

Figure 1: Basic Structure of WSN

2. Design Factors and Open Issues in WSN

The design and development of WSN is associated with different factors such as fault tolerance, power consumption, scalability, node deployment, connectivity, coverage, QoS, hardware constraints etc.

2.1. Power Limitation

Sensor network is highly acceptable in most of the real world and engineering application because of its limited battery power feature. But still the communication phase consumes more power in WSN than its data storage and data processing phases. Most of the applications of WSN expect the lifetime of the sensor network to be for few months to years because; it is almost impossible and expensive to recharge or to replace the batteries. So the only way to improve energy efficiency in WSN is by reducing power consumption (see [9]).

2.2. Node Deployment

Node deployment refers to defining optimal position of sensor nodes and base station (optional) in vast applications, so that the energy efficiency, network lifetime, quality of service, connectivity and coverage of the network could be highly enhanced with fewer sensor nodes. Sensors in WSN would be placed by two methods: deterministic and non-deterministic placements (see [10]). In deterministic placement method, sensor nodes are exactly placed in the predetermined locations after calculating the specific positions based on the applications. Few examples of deterministic deployment of sensor nodes would be in building and structural monitoring, medical applications, underwater acoustics and smart grid monitoring. Whereas in other applications such as battlefield surveillance, disasters monitoring and habitat monitoring where the prior prediction of sensor location is not possible, the most adoptable sensor placement strategy is random or non-deterministic deployment. In sensor network, covering n-target points with minimum number of nodes is proved as NP-Complete problem.

2.3. Localization

The method of discovering sensor node position is generally referred as localization. Basically in most of the localization techniques, few GPS enabled sensor nodes who know about its co-ordinates are deployed. These sensor nodes transmit its co-ordinates along with the beacons to the nearby sensors to localize themselves. However in application such as target tracking, only if the user retrieves the exact location information of the sensor node, the job can be accomplished. Besides, an outline of localization method for sensor network is explained in (see [11]).

2.4. Node Scheduling

The sensor nodes lifetime expectation should be appreciably high because frequent charging or changing battery is almost impossible for applications such as habitat monitoring. Hence optimal power consumption of the sensor nodes are the urgent need of the hour. Improving network lifetime and deteriorating power consumption can be highly possible by putting part of the sensor nodes into sleep mode and others remain in the active state. The sleeping nodes wake up periodically for transmission and reception of the sensory data. Hence a better scheduling mechanism should be there to decide the ideal time for the sleep and wake up states for the sensor nodes. Moreover to improve the network lifetime of the network cluster based topology is followed in which cluster head selection and rotation of the cluster head is also quite challenging. Such a topology configuration technique needs an energy efficient scheduling method (see [12]).

2.5. Quality of Service

There are few applications in which the data gathered should be transmitted instantly as it is sensed by the sensor. Those are all time constrained applications and the quality of the data matters in this case. In certain applications where the sensor network is deployed in some remote locations, the network lifetime is crucial and here the quality of the data becomes trivial. Suppose the energy is depleted more because of poor QoS support, the network lifetime will be affected proportionally. Thorough analysis of QoS requirement for various WSN applications is studied and subsequently QoS support is provided to the sensor network to meet the above said challenges. A survey of QoS support strategies used in WSN is described in (see [13]).

2.6. Data Aggregation

Based on the applications, sensor-nodes are thickly populated and due to this huge amount of data are generated. The primary issue raised here is efficient collection of gathered data. In addition to this the chance of data redundancy is more while gathering the data from various sensors. Since the data transmission consumes more power, data gathering has to be done by eliminating significant redundant data to lessen the number of transmissions (see [72], [73]). Consequently the energy efficiency of the network could be improved and data transfer would be optimized for the routing protocols.

3. Paradigms of Swarm Intelligence: A Brief Overview

SI is a unique field which is the study of groups of simple agents that enable intelligent behavior in complex environments (see [20]). The agents are as simple as the natural systems such as collective intelligence of social insects and birds to solve distributed problems. SI includes models that show the capability to acquire knowledge and adapt to different circumstances (see [14], [15],[16]). On the other hand, SI can express scalable and adaptive behaviors by designing autonomous distributed systems. Almost all the SI techniques evolved so far, are from the natural biological systems such as termites colonies, swarm of birds, swarm of bees etc. The basic idea behind the formation of such natural system is that for better foraging in swarm of honey bees, finding the optimal path to their food source in colonies of ant kindled the minds of researchers to design novel distributed algorithm for optimization and approximations. This cooperative nature of unsophisticated agents helps actually to resolve routing problems. Among the group of agents a single agent try to discover the food source and once the process got succeed it will build a path between its colony and the food source by moving back and forth. Eventually the other agents acquire the information either directly (i.e. by waggle dance in honey bees) and indirectly (i.e. by pheromone intervene communication in termites) from the sample path established by the original agent (see [17]).

3.1. Ant Colony Optimization (ACO)

The basic ACO is an optimization algorithm based on the natural intelligent behavior of ants (see [18]). The foraging nature of certain ants has highly influenced the ACO. The ants randomly start searching to find the food source. During its search when a single ant locates the food source it examines the amount of the food and brings a few portion of the food to its colony. This process is repeated for the other ant which finds a food source. The ants deposit a chemical substance called pheromone on the ground towards its colony while returning from the food source. The other ants in the colony evaluates the pheromone content of the food carrying ant and based on the quantity of the pheromone on the paths they align themselves towards the path of excess food source. Initially the ants explore the food source with multiple paths. In due course based on the strength of pheromone content, the shortest path gets higher transfer rate due to its indirect information exchange. The artificial ACO iterative algorithm imitates the same behavior of biological ants to resolve combinatorial optimization problems. Assume there are two ways X and Y between the food source and ant colony. Let $N_X(t)$, and $N_Y(t)$, be the group of ants forage towards the food source at time t. The probability of path X at time $t+1$ is set as,

$$P_X(t+1) = \frac{(d_a + N_X(t))^k}{(d_a + N_X(t))^k + (d_a + N_Y(t))^k}, \tag{1}$$

Where

$$P_X(t+1) = 1 - P_Y(t+1), \tag{2}$$

d_a, is the attraction degree and k is the basic bias.

The colony construction behavior of biological ants is also popular because of its self-organizing nature. By the secretion of a chemical substance, the ants communicate each other. During this random exchange, if this chemical substance is finding to be same between two ants, they are associated with the same colony. This colonial closure model is adopted in the artificial ant based clustering algorithm. In addition to this the biological ants greedy migration property is used for sensor deployment. The ACO algorithm is first targeted to solve the well-known TSP problem, which is a NP-hard problem. After its success, ACO have applied to solve routing issues, scheduling issues and so on in telecommunication networks.

3.2. Honey Bee Optimization (HBO)

The natural foraging behavior of the honey bee has provoked the evolution of honey bee optimization algorithm. In the year 2005, Karaboga has introduced artificial honey bee colony algorithm in mathematics for numerical optimization (see [21]). The bee swarm contains three elements, employed bees, unemployed bees (onlookers and scout bees) and food source. Recruitment of unemployed bee for foraging is the crucial part of the algorithm. The employed bees which visit the food source unload the nectar in the comb; moreover it examines the properties of food source such as the quantity of nectar, nectar taste, distance between food sources to hive, direction etc., and carries the news to share it with waiting or unemployed bees in the hive. The information exchange happens in the dancing area of the hive. The employed forager shares the information through waggle dance in the dancing area. Such current source of food is shared by all the employed bees; this aids the onlookers to select the best gainful food source. This is the recruitment phase in the foraging behavior of honey bees. Of course the onlookers employ it for foraging is proportional to the richest food source (see [22]).

In honey bee colony optimization algorithm, the optimized solution for the problem is finding the position of food source. At first assume all the scout bees have reached the food source. So they all will act as employed bees. Consequently the collection of nectars starts and eventually there will not be any remains. Thereafter the employed bees become scouts and perform random search of food (see [23]).

The general steps of BCO algorithm is given below,

repeat

1. Employed Bees Phase: Employed bees evaluate the fitness of different food source and find the optimum solution. This is shared among the onlookers through waggle dance.
2. Onlooker Bees Phase: Information gained from employed bees helps onlookers to select the best food source through roulette wheel selection method.
3. Scout Bees Phase: When the food content is abandoned, the employed bees become scouts. Again random searching of food takes place among scouts.
4. Store the optimum solution achieved

until maximum CPU time or maximum number of cycle

3.3. Particle Swarm Optimization (PSO)

PSO mimics the behavior of swarm of birds moving to attain optimized solution for a problem. Every entity in the flock has a position and velocity vector to denote the candidate solution (see [24]). Besides, every agent has small storage unit to memorize its local best position and a global best position, projected through its neighbor agents. The crucial part of PSO is to locate the best particle position.

PSO consists of a flock of agents, where each agent represents a potential solution. In the initialization phase of PSO, each entity is assigned with random values for position and velocity that travel in an n-dimensional hyperspace in search of best solution. An individual agent i occupies velocity V_{ik}, and position P_{ik}, in the k^{th}, dimension of the hyperspace, $1 \leq k \leq n$, and $1 \leq i \leq a$,. In each generation phase of PSO, the agents best position $pbest_{ik}$, and the global best position of the agent $gbest_k$, is memorized. In every iteration m, velocity V and position P are updated by equation (3) and (4). This procedure is continued until either a suitable $gbest$ is reached or a fixed number of iterations m_{max}, is reached.

$$V_{ik}(m+1) = w.V_{ik}(m) + c_1.r_1.(pbest_{ik} - P_{ik}) + c_2.r_2.(gbest_k - P_{ik}), \quad (3)$$

$$P_{ik}(m+1) = P_{ik}(m) + V_{ik}(m+1). \quad (4)$$

Here, c_1, and c_2, are learning factors, and r_1, and r_2, are random numbers between 0 and 1, w is the inertia co-efficient between 0.2 and 1.2.

4. SI Techniques to Override WSN Challenges

The low cost, miniature size of sensor node have made easy to employ large number of it for various applications. On the other hand, WSN face some technical challenges such as topological issues, energy issues, connectivity and coverage issue, localization issues and QoS issues. Among the above issues energy efficiency is a crucial one, which could apparently deteriorate other properties of sensor network. The SI techniques explained above are all exploited in WSN to overcome its real-time issues.

4.1. Efficient Design and deployment in WSN

WSN design and deployment is a difficult job which relatively influences the performance of WSN in terms of cost, quality and network lifetime. WSN deployment is to find the optimal location, where the sensor nodes or the sensor base station could be placed. SI algorithms are highly useful in solving the design and development issues of WSN. The foremost objective of sensor node deployment algorithms is to improve energy efficiency, coverage and connectivity. Based on the applications, the design of sensor networks can be static or dynamic. In case of static sensor network, the topology creation or the deployment will be deterministic, on the other hand for dynamic sensor network, topology is created non-deterministically. For both the topology creation plan, clustering is a well-known and recognized technique to bring up a connected hierarchy and to improve the energy efficiency, thereby prolonging the network lifetime (see [25]).

4.1.1. ACO based design and deployment

ACO-Greedy has been proposed for sensor node deployment in (see [19]), where the greedy migration method of ant colony had been followed to achieve full coverage and to cut the deployment cost. Furthermore by assigning dynamic communication range to the sensor nodes, the network lifetime and network cost can be improved. The primary goal of the paper is to enhance grid based coverage and low cost connectivity (GCLC) by avoiding energy-hole problem and by optimally choosing sensor nodes to cover predefined Point of Interest (PoI). ACO-greedy is the first approach in WSN which mimics the greedy migration property of biological ants. Basically the sensing area comprises distinct grid points which may win to become possible location to deploy sensor nodes. Initially the ants migrate from one grid to another and the grid visited by the ants will succeed to get sensor node to be deployed there. In due course, each and every organized node would be interlinked to achieve connectivity.

Minimum-cost and connectivity guaranteed grid coverage (MCGC) is another critical issue in sensor network deployment which could be sorted by efficient design and deployment algorithm. MCGC is agreed to be a combinatorial optimization problem and hence an improved ACO based algorithms EasiDesign has been exploited to solve the above said issue (see [26]). In EasiDesign, the ants are allowed to move in the sensing field and place the sensor in the right critical candidate point selected based on the pheromone content on the link. Each ant produces its own solution and the solution with less number of sensor nodes is saved. This is continued until the best solution is reached. The deployment approach is distributed in EasiDesign, since the deployment solution is individually produced by each ant.

EASIDESIGN DEPLOYMENT ALGORITHM

Table 1: Summary of SI Applications in WSN Deployment

SI based Techniques	Algorithm/ Article No.	Deployment: Deterministic/ Non deterministic	Node Type: Mobile /Static	Study	Objective
Ant Colony Optimization	ACO-Greedy (see [19])	Deterministic	Static	Simulation (Visual C++ 6.0)	Min. deployment cost, Max. network lifetime
	EasiDesign (see [26])	Deterministic	Static	Simulation and Real deployment	Min. cost connectivity
	ACO-TCAT (see [27])	Deterministic	Static	Simulation (Visual C++)	Min. cost, Max. coverage and connectivity
	HGSDA(see [28])	Both	Mobile	Simulation (Matlab)	Min. moving distance and max. coverage
Honey Bee Optimization	ABC-Deployment* (see [32])	Deterministic	Static	Simulation (Matlab)	Max. network lifetime
	ABC-Dynamic Deployment* (see [34])	Non-deterministic	Both	Simulation	Max. coverage
Particle Swarm Optimization	Improved DPSO(see [35])	Non-deterministic	Mobile	Simulation	Max. coverage
	IPSO(see [36])	Non-deterministic	Both	Simulation	Min. energy consumption, Max. coverage ratio
	VFCPSO(see [37])	Non-deterministic	Both	Simulation (Matlab)	Max. coverage
Hybrid approach	PSGO(see [38])	Non-deterministic	Both	Simulation	Max. coverage

*This algorithm is referred by author by this name

repeat
  Each ant selects the beginning point randomly
  repeat
    Probabilistically select the next location
  until all the ant produces its own solution
  Save the minimum cost solution
until maximum number of iterations

Choose the best solution from the saved solution.

The above Easidesign is based on only one class of ant transition. ACO-TCAT (see [27]) is one another version of ACO algorithm with three classes of ant transition is proposed to solve MCGC problem of WSN. The ultimate aim of this algorithm is to increase quality of solution space and to improve the searching speed. Initially the ant is on the sink and it is allowed to move from one grid to other. The grid points visited by the ant are all the point of solution (PoS). ACO-TCAT is able to solve the MCGC problem by detecting PoIs with optimal number of PoS, provided all PoS associated with sink.

HGSDA (see [28]) is a hexagonal grid plot method to accomplish full network coverage. After the random deployment of sensor nodes this algorithm segregates the target area into simple hexagonal grids. Then apply ant colony optimization algorithm in such a way if there is more than one node in a hexagonal grid, choose it and deploy it in other hexagonal grid centre which has no sensor node to monitor. The ant colony algorithm guarantees reduced moving distance of sensor nodes thereby reducing the energy consumption of the whole sensor network.

4.1.2. HBO Based Design and Deployment

HBO algorithm is used by Mini et al. (see [30]) to overcome simple coverage problem in WSN. Using the same approach Mini et al. have extended their work to resolve Q-coverage and k-coverage issues in WSN (see [31]). From the perspective to provide better network lifetime and to solve target coverage problem in WSN, artificial honey bee colony algorithm is used in (see [32]). The work is targeted for applications in which the PoIs is known in prior. For such deterministic deployment, the upper bound of the network lifetime is calculated mathematically as in (see [33]).

$$U_n = min_j \frac{\sum_i M_{ij} * b_{i'}}{q_j}, \tag{5}$$

where $q_j = k$(k-coverage), M_{ij} is the coverage matrix, $b_{i'}$ is the battery lifetime. The nodes are randomly deployed initially with population B. Among the neighbour, select the best solution and it is repeated for all other nodes. If there exist a new solution better than the old one, save the new solution and the old solution is discarded. Using equation (5) the optimal deployment positions are decided in base station.

On the basis of probabilistic detection model (see [34]), a novel dynamic deployment of both static and mobile sensor nodes is proposed to improve the coverage area. In this model PoI is covered by different probabilities. In case when a single PoI is mapped to individual sensor, the coverage and the network reliability will be considerably low. Hence overlapping target coverage is the urgent need for dynamic deployment. This is accomplished by the above said probabilistic detection model through ABC algorithm.

4.1.3. PSO Based Design and Deployment

Topology control of WSN is ensured by three factors: coverage, connectivity and network lifetime. Among this factor, the basic factor is coverage and it is achieved in (see [35]) though an improved discrete PSO approach. The major advantage of this algorithm is to reduce the nodes moving distance thereby reducing the energy cost. This is achieved through two important phases:

i) Deployment planning i.e., designing and determining the candidate position of the sensor node for a particular sensing area.

ii) Movement control i.e., Fine tuning the position of the randomly deployed sensor nodes to achieve optimal energy cost.

In (see [36]), the node deployment issue is addressed by a virtual force (VF) algorithm and an enhanced PSO algorithm is used to overcome energy consumption issue and coverage ratio issue. This algorithm converge the position of mobile sensor nodes and also guarantees maximum network survival time.

Wang et al. has proposed (VFCPSO) a new approach of virtual force based PSO algorithm (see [37]). In this method a sensor node is moved multiple times by the virtual force of any other sensor node to attain better coverage ratio. In (see [38]) the deployment factors are considered for both static and dynamic nodes. Its a hybrid algorithm which integrates the property of both PSO and genetic algorithm to solve network holes. The mobile nodes locations are adjusted mainly to achieve quality of service. Selection and mutation operations are imported to PSO and the result shows better QoS improvement over coverage.

4.2. Energy Aware Node Clustering in WSN

Battery limitation is one of the major problems in sensor nodes. Once the sensor nodes are deployed in remote locations, recharge and change of battery is not an easy task. Hence energy efficiency is one of the crucial objectives to improve the lifetime and connectivity of the sensor network (see [39]). Compared with data processing, data communication consumes more power. Therefore it is necessary to lessen the long distance transmission. It is discussed in (see [40]), that an efficient network topology is essential for better coverage, scalability, reliability, better network lifetime. Node clustering is a significant topology management strategy to reduce the distance of data transmission (see [42], [92]). The nodes in the entire sensing area are divided into several clusters with one node as Cluster Head (CH) in each cluster and the remaining nodes are

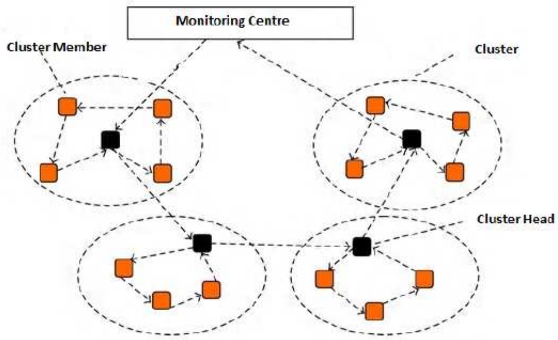

Figure 2: Clustered WSN

Cluster Member (CM). It is the responsibility of the CH to collect all the sensed data from its CMs and send it to the BS directly or via other CHs (see [43]).

LEACH (Low Energy Adaptive Clustering Hierarchy) (see [44]), is one of the famous clustering algorithms for sensor networks. Clusters are formed based on a distributed algorithm and the CHs are selected randomly. This algorithm has its own drawbacks. Since the CHs are selected randomly, the chance of sensor node accumulation to a particular region will be more. Also the algorithm doesnt care about the distance between CHs to base station. These issues in turn increase the energy consumption of the network. In (see [45]) the authors explained about the CH re-election process of LEACH. Since CH role change is probabilistic, the probability for a low energy node to become CH is more. Practically this should not occur because this will drastically reduce the reliability and lifetime of the network. Extensive work is going on to resolve node clustering problem using SI techniques (see [41]).

4.2.1. ACO Based Clustering

IC-ACO (see [46]), uses ACO algorithm to reduce the redundant data within the cluster. The algorithm has two phases. Cluster head selection is the first phase of the algorithm. Redundant data transmission is the second phase of the algorithm in which a particular sensing radius S_r is selected. Among the nodes within the chosen sensing radius, the highest energy node is selected to transmit the data to CH. Rest of the node among the assumed sensing radius S_r will be in the sleeping state. This ant based optimization algorithm will provide optimum path to base station through probabilistic approach.

An efficient cluster based routing algorithm was proposed in (see [47]), for

Table 2: Summary of SI Applications in WSN for Node Clustering

SI based Techniques	Algorithm/ Article No.	Clustering Methodology	Node Type: Mobile /Static	CH selection (random /BS)	Study	Objective
Ant Colony Optimization	IC-ACO(see [46])	Distributed	Static	Random	Simulation	Energy saving
	ACO-cluster* (see [47])	Distributed	Any	Random	Simulation (Xmulator)	Energy saving, better load balancing
	ACO-C(see [48])	Centralized	Static	By BS	Simulation (Matlab)	Energy saving
	ACO-uneven cluster*(see [49])	Distributed	Any	Random	Simulation (Matlab)	Max. network lifetime
Honey Bee Optimization	WSNCABC (see [50])	Centralized	Static	By BS	Simulation (Matlab)	Min. energy consumption
	ICWAQ(see [51])	CH selection: Centralized Working: Distributed	Static	By BS	Simulation (Matlab)	Optimum CH, Min. energy consumption
	Clustering-SIC* (see [52])	Distributed	Static	Random	Simulation (Matlab)	Min. energy consumption
Particle Swarm Optimization	PSO-C(see [53])	Centralized	Static	By BS	Simulation (NS2)	Max. network lifetime
	PSO-MV(see [55])	Distributed	Any	Random	Simulation (Matlab)	Max. network lifetime
	PSO-SD(see [56])	Semi-Distributed	Static	Within cluster	Simulation (Network Simulator)	optimizing CH location

*This algorithm is referred by author by this name

large scale sensor network by ACO. This procedure has two level routing. Intra cluster members transmit the sensed data directly to CH in the first level. In the next level CHs transmit data to the base station through optimal path using ACO. This results in better load balancing, optimum routing overhead, reduced power consumption, and less data transmission time.

In ACO-C (see [48]), a novel cluster based routing algorithm was proposed using ACO. This algorithm is used to reduce long distance data transmission using an efficient cost function at the base station. In (see [49]), an uneven clustering algorithm based on ACO was proposed to find best fit route between cluster heads.

4.2.2. HBO Based Clustering

In WSNCABC (see [50]), a novel swarm based HBO algorithm was proposed to reduce energy consumption of the sensor network. In conventional clustering algorithm the main factor considered to select the CH is the residual energy. But in this approach in addition to energy, distance between the sensor nodes to base station is also taken into account. A distance table is maintained to hold this distance values. Hence the fitness function considered here is given in (6).

$$F = \sum_{j=1}^{n} (\sum_{i=1}^{m_j} D(SN_i, CH_j)^2 + D(CH_j, BS)^2), \quad (6)$$

where the distance function *D(SN, CH)* is the distance between sensor node to cluster head and *D(CH, BS)* is the distance between CH with base station.

Karaboga et al. in (see [51]) has proposed a centralized cluster based routing using HBO algorithm. The clustering approach is same as the conventional LEACH protocol in which data aggregation in every cluster will be handled by the respective cluster heads. Karabogas clustering approach deviate from LEACH in the CH selection process. In LEACH CH election is random whereas in this proposed algorithm CH election is HBO based.

A decentralized clustering algorithm is used in (see [52]) based on social insect colonies. In WSN CH are same as queen and cluster members are workers of the social insect colony. CHs are selected based on the local and global control packets. In this approach clusters are arranged as concentric layers with CH at the centre as given below. This multiple layer approach helps to reduce the communication distance between sensor nodes and also reduces the data collection time.

4.2.3. PSO Based Clustering

PSO-C (see [53]), is centralized clustering methodologies which take into account both remaining energy and distance between sensor nodes and CHs. Its fitness function is denoted as,

$$F = \beta F_1 + (1 - \beta) F_2, \quad (7)$$

where F_1 is the optimum Euclidean distance between sensor node and CH and F_2 is the optimal remaining network energy. These PSO based work performs better than LEACH, LEACH-C, GA and K-means clustering algorithms.

In MST-PSO (see [54]) the sensor nodes and CHs involve in multi-hop data communication. In this method, the WSN is considered as weighted graph and its distance based minimum spanning tree is calculated. The best path to route the packets from a node to its CH is computed to predict the optimal energy consumed path. PSO is used in this work for CH re-election and for routing finally to achieve longer network lifetime.

Based on PSOs fitness function optimization in (see [11]), the proposed work is able to provide a balanced energy usage throughout the network. An improved PSO algorithm, PSO-MV (PSO-Master and Vice CH) is followed to elect a master CH and a vice CH in each cluster, then the work is shared to both master and vice CHS. This approach could achieve better energy balance among all the nodes. Another variant of PSO, a semi-distributed approach is carried in (see [56]) where the PSO algorithm is applied within a cluster to increase the lifespan of the entire network.

4.3. Energy Aware Scheduling in WSN

Sensor node scheduling as said in (see [57]) is one another common method followed to improve the lifetime. It is wisely attained by reducing the energy consumption of sensor node through sleep-awake process. This is by exposing few nodes to active state and other to sleep state. The sleep mode sensors consume very negligible power for its low-power timer to awake the sensor if needed. The wakeup scheduling schemes are broadly classified as synchronous and asynchronous based on time synchronization (see [58]). Synchronous scheduling is internally classified as periodic and aperiodic.

4.3.1. Node Scheduling Using ACO

Bio-inspired scheduling system is projected in (see [59]) to reduce discrepancy in sensing coverage. This adaptive technique is similar to a selective on-off method to monitor rare targets. The different functional modes of the sensor nodes are mimicked from the biological factors of the ant colony. Figure 3 shows the different states of sensor nodes and its switching conditions. The sensors are intelligently and conditionally switched to any one of three states namely, active, sleep and sniff. Energy consumption of sniff mode is lesser followed by the sleep mode. Among the three modes, active mode energy consumption is higher. By this approach this method is able to reduce the energy consumption considerably.

Objective of TPACO (Three Pheromone ACO) (see [60]) is to free up efficient-energy coverage (EEC) problem in WSN by a new ACO algorithm. The novelty in this algorithm is that, this approach exploits the three different pheromone properties of ants for time based scheduling, instead of using only one pheromone property. Among the three kinds of pheromones the first local pheromone aids the agents (ants) to self-organize, with lesser sensors. The other two global pheromones help to organize optimal active number of sensors

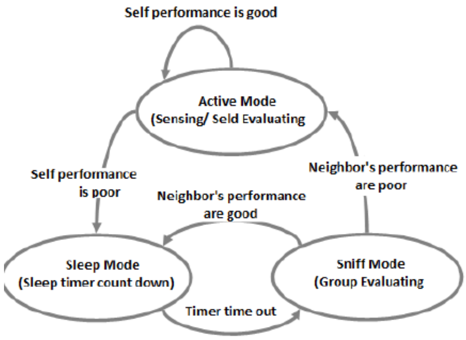

Figure 3: Bio-inspired Scheduling: State Diagram

to each PoIs and to form a better sensor set.

ACB-SA (ant colony based scheduling algorithm) in (see [60]) is proposed to overcome EEC issue. This algorithm use probabilistic detection model to sense the event at POIs. Unlike the conventional ACO algorithm, the ACB-SA is optimized to resolve the coverage problem. But the energy hole problem is not handled in this work.

In (see [61]) ACS-SM is proposed to increase the lifespan of heterogeneous WSN. The heterogeneous sensor network is able to do multiple sensing tasks because it has various sensors to detect temperature, pressure, moisture etc. in one module. A novel ACO variant is applied in this model to allot only the necessary amount of sensor nodes to be active state to carry out the sensing task and others to be sleep state. So this technique has a subset of sensor nodes for monitoring the region of interest. This bio-inspired algorithm is used to solve EEC problem based on Boolean sensing model. But the algorithm lags to handle practical sensing model.

4.3.2. Node Scheduling Using PSO

To the best of our knowledge, node scheduling problem in WSN using HBO based algorithm is almost unexplored research area.

In EBSS-PSO (see [62]) is energy balanced scheduling scheme based on PSO. In this approach the power is shared among the sensing and data communication process to minimize overlapping area and to improve the coverage. The method effectively computes which node to be active mode and which nodes to be in sleep mode. The results are compared with other scheduling schemes to prove that the EBSS-PSO scheme considerable improves the clusters lifespan.

Table 3: Summary of SI Applications in WSN Scheduling

SI based Techniques	**Algorithm/ Article No.**	**Centralized /Distributed**	**Scheduling Scheme**	**Node Type: Mobile /Static**	**Study**	**Objective**
Ant Colony Optimization	Bio-inspired-Scheduling* (see [59])	Distributed	Selective on-off	Any Mobile target	Simulation (Matlab)	Min. energy consumption
	TPACO(see [29])	Centralized	Periodic	Static	Simulation (Matlab)	Max. energy efficient coverage
	ACB-SA(see [60])	Centralized	Periodic	Static	Simulation (Matlab)	Better coverage and connectivity
Particle Swarm Optimization	EBSS-PSO(see [62])	Distributed	Probabilistic	Static	Simulation (Matlab)	Max. energy efficiency
	SSM-PSO(see [63])	Semi-Centralized	Binary encoding	Static	Simulation (Matlab)	energy efficient coverage
Hybrid Approach	HA(see [64])	Semi-Distributed	TDMA	Static	Simulation (C++)	Max. energy efficiency

*This algorithm is referred by author by this name

In SSM-PSO (see [63]), the authors proposed node collaborative sleep algorithm based on PSO to decrease the redundant node in the network, thereby the network lifetime could be increased. By specifically scheduling the sleep control property, the power utilization is drastically reduced. TDMA based scheduling of sensor network is handled in (see [64])to save the power consumption in the network. It is a hybrid approach combining both PSO and genetic algorithm. In TDMA, basically proper time slots are allotted to sensor nodes to transmit the sensed data. The main objective of this time allocation is to schedule the sensor nodes in an optimal way.

4.4. Localization in WSN

As explained in (see [65], [66]), localization is an important research scope in WSN as the nodes are thickly and randomly deployed in the remote locations. There are two broad classifications in localization algorithm, such as range based and range free (see [90]). Range based scheme of classification uses the physical measurements like, Time of Arrival (ToA), Received Signal Strength (RSS), distance and angle. On the other hand range free technique uses connectivity information like, neighbourhood and hop count. Another classification is based on localization mechanism as, centralized and distributed (see [91]). It is not possible to use GPS in each of the nodes, because of its critical factors such as energy usage and cost. Hence swarm intelligence variants such as ACO, HBO and PSO are greatly used to find the node location.

Table 4: Summary of SI Applications in WSN Localization

SI based Techniques	Algorithm/ Article No.	Anchor based/ anchor free	Localization mechanism	Node Type: Mobile /Static	Study	Objective
ACO and HBO	ACA localization* (see [67])	Anchor based	Distributed Range based	Static and Mobile beacon	Simulation	Location accuracy, max location coverage rate
	BOA localization* (see [68])	Anchor based	Distributed Range based	Any	Simulation	Best Location accuracy
PSO	PSO localization* (see [69])	Anchor based	Centralized Range free	Static	Simulation (Matlab)	Minimum localization error
	PSO and BFA based localization* (see [70])	Anchor based	Distributed Range based	Static	Simulation (Matlab)	Energy optimization, minimum localization error
	PSO and CLPSO based localization* (see [71])	Anchor based	Distributed Range based	Static	Simulation	PSO: less Computation time CLPSO: More accurate

*This algorithm is referred by author by this name

4.4.1. ACO and HBO Based Localization

ACA based localization strategy in (see [67]) considered one mobile beacon and several static nodes. Mobile beacon is used in this localization process as virtual beacons which send beacon packets to unknown nodes. The range based location information $(x_i,\ y_i)$ and RSS_i of mobile beacon packet is used to find the location of the unknown node. Ant colony algorithm is adopted to find the optimal path (mobile beacon trajectory). An optimal filtering procedure is followed to enhance the location accuracy, reduced energy consumption and maximum localization coverage.

In (see [68]), an artificial HBO based algorithm is applied to find the location of sensor node. The range based measurements such as Time of Arrival (ToA) and Received Signal Strength (RSS) are calculated with respect to reference node, which helps the unknown node to find its location. This work extended for multistage localization problem and its performance is compared with single stage localization. A population based search algorithm based on bio-inspired bees optimization is followed here. This work is based on food seeking behaviour of natural honey bees.

4.4.2. PSO Based Localization

Using PSO a localization technique is applied for WSN to predict the node location (see [69]). The main idea of this work is to find the *(x,y)* co-ordinates of n target sensor nodes among m nodes with the help of a priori information of position of m-n beacons. This PSO algorithm works on a centralized architecture of sensor networks that too on the base station, to reduce the localization drawback given as,

$$f(x,y) = \frac{1}{M}\sum_{i=1}^{M}(\sqrt{(x-x_i)^2+(y-y_i)^2}-d_i). \tag{8}$$

In the above expression *(x,y)* is the coordinate of target node to be finalized, (x_i, y_i) is the coordinate of anchor location, $M \geq 3$ depicts the anchor number, d_i is the distance from beacon i. The performance parameters of this work is compared with simulated annealing results and confirmed that PSO based localization has more than fifty percentage less localization error.

Distributed localization approach in (see [70]), targeted to achieve energy aware better localization using both the features of PSO and bacterial food searching algorithm. In a continuous plane space, each sensor node runs this bacterial food searching algorithm to determine its *(x,y)* co-ordinates. The node that got three or more beacons will execute PSO algorithm to reduce localization error. The sensor node which got positioned using beacon in i^{th} iteration will become beacon in $i + 1^{th}$ iteration. Compared to bacterial food searching algorithm, PSO works faster, but more memory intensive.

A distributive localization technique is proposed(see [71]), by PSO and CLPSO (Comprehensive Learning PSO). Here the localization of sensor node is modelled as multi-dimensional optimization problem. The performance metrics such as total number of sensor nodes localized, localization error and computational time are analysed and compared for both the algorithm and confirmed that localization using PSO is faster and localization using CLPSO is accurate.

4.5. Data Aggregation in WSN

Sensor nodes are highly deployed to monitor the wide range of remote applications from habitat monitoring, smart grid monitoring to disaster monitoring and so on. In conventional method the sensed data from all the nodes should reach the base station. Among all the function in WSN, data communication consumes more power. By exploiting data aggregation technique in WSN, data redundancy is highly minimized and power consumption can be reduced (see [74], [75]).

4.5.1. ACO Based Data Aggregation

An energy constraint sensor network attained in (see [76]) by adopting tree based in-network data aggregation in multi-hop communication model. Data fusion is carried out prior to transmission at some aggregate points and this ultimately reduces the data quantity and positively the energy consumption. The above said data aggregation process is based on ACO and it is named as ant-aggregation algorithm which develop low cost aggregation trees. Forward ant will try to find shortest route to destination and end the iteration or it will try to find closest aggregation point and end the iteration. This proposed process converges to the local best aggregation tree.

The previous work is prolonged in (see [77]), by saying that the probability of aggregation point selection is not optimal. To overcome this issue, path extension idea is proposed, so that many possible routes may meet each other. This method also has the additional feature of having overlapping nodes. Consequently the communication will be towards the aggregation point or through overlapping nodes to minimize in-network traffic.

An ACO variant DAACA is proposed for data aggregation in (see [78]) which has three stages: initialization, data transmission and operations on pheromones. During data transmission stage each node predicts the next hop by calculating residual energy and pheromone content of nearby sensor nodes. Evaporating and depositing nature of pheromone is combined for pheromone adjustment which helps to improve the network lifetime.

4.5.2. PSO and other SI Based Data Aggregation

A modified PSO (see [79]), jumping particle swarm optimization (JPSO) is proposed to handle multi-objective steiner tree problem (MOSTP). The main objective of this work is to find finest spanning tree for energy efficient data aggregation in WSN. A novel SI technique, elephant swarm optimization (ESO) is applied in WSN (see [80],[81]) to achieve energy aware data aggregation. Both the work emphasis cluster formation with a co-operative processing to improve the reliability and efficiency of data aggregation.

Table 5: Summary of SI Applications for Data Aggregation

SI based Techniques	Algorithm/ Article No.	Organization type	Aggregation mechanism	Node Type: Mobile /Static	Study	Objective
Ant Colony Optimization	Ant-Aggregation (see [76])	Tree	Distributed	Static	Simulation (Matlab)	Max. energy efficiency
	ACA*(see [77])	Tree	Distributed	Static	Simulation	Min. data delivery energy
	DAACA(see [78])	Tree	Distributed	Static	Simulation (Java)	Max. network lifetime
Particle Swarm Optimization	JPSO-Double (see [79])	Tree	Distributed	Static	Simulation	Optimal spanning tree, min. energy consumption
Elephant Swarm Optimization	ESO(see [80])	Cluster	Distributed	Static	Simulation (Matlab)	Max. network lifetime
	ESB(see [81])	Cluster	Distributed	Any	Simulation (Matlab)	Max. network lifetime

*This algorithm is referred by author by this name

4.6. Quality of Service in WSN

QoS signifies, the quality remarked by the end user, throughout the usage of network service, in terms of bandwidth, fairness, less packet loss, and jitter. Figure 4 depicts a simple QoS model. QoS surety in WSN has some important challenges such as, resource constraint, dynamic network topology, redundant data, power consumption etc., (see [82]). SI techniques are currently applied extensively in WSN for QoS management.

4.6.1. ACO Based QoS Management

To improve the network lifespan and to reduce energy consumption, an ACO based QoS routing algorithm is proposed in (see [83]). This method is used to optimize the ACO algorithm more quickly. It has three phases of work as follow:

i) Forward ant phase: The ants will take all the available paths to reach the destination.

ii) Backward ant phase: The forward ants act as backward ant after reaching the target node. It helps to discover optimal path.

iii) Maintenance of routing: The routing algorithm is still continued in this phase, due to any miserable failure in standby node.

In (see [84]), an ant colony based QoS routing algorithm (AntQHSeN) is

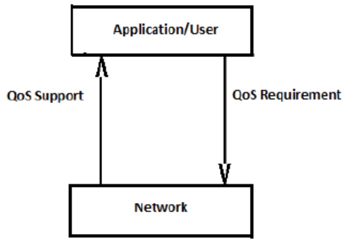

Figure 4: Simple QoS Model

proposed to solve QoS challenges in heterogeneous WSN. This work adopts admission control procedure to achieve optimal bandwidth. The authors considered a multimedia-WSN in (see [85])and proposed a QoS assured routing scheme using ACO (AntSensNet). In addition to image data, the video data is also taken into account for routing. To achieve negligible video distortion during data communication, an effective multi path video data scheduling is incorporated in AntSensNet.

4.6.2. PSO based QoS management

QoS factors get weakens badly during network routing. An improved PSO algorithm is proposed in (see [86]), to solve the QoS challenges in WSN. In this proposed algorithm each possible routing path is considered as an individual/particle. The main objective is to find the optimal position of the particle through effective evaluation. The finest position of the individual is the ultimate goal of the algorithm. In (see [87]), the authors have targeted multicast routing problem through a hybrid approach, combining both PSO and ACO algorithms. In this hybrid algorithm, the each iterations solution in ACO is subjected to position update and velocity update using particle swarm optimization. Hence the current solution of ACO becomes current best solution through PSO. The outcome of PSO is used to update the pheromone in ACO and the process continues till it reaches an optimal best solution.

ACO-PSO Algorithm

repeat

1. ACO start from source node
    1.1. Ant sub colony n arrive destination node
2. PSO start

    2.1. Velocity and position update
  3. Pheromone update
until maximum number of iterations
Choose the best solution from the saved solution.

A hybrid SI based algorithm (HACOPSO)(see [88]) is to resolve QoS multicast routing problem. This will build a low cost multicast routing tree which guarantee QoS metrics like data loss rate, jitter, delay and bandwidth. The same work is extended in (see [89]) to achieve optimal tree cost.

5. Conclusion and Future Directions

The development of large scale WSN has its own success in wide range of applications such as environment monitoring, habitat monitoring, military applications and many industrial applications, because of its self-organizing, low cost, reduced size and untethered nature. On the other hand, the sensor nodes are resource constrained devices with limited battery and bandwidth. In most of these applications numerous sensors nodes are remotely deployed and they are set to operate autonomously. Hence after deployment, battery replacement is not practical. Battery limitation in turn affects the network lifetime, coverage and connectivity in WSN. To overcome these issues, the prime need is an energy efficient sensor network.

Recent literature shows that energy efficiency can be improved in the following functional stages of WSN such as, design and deployment, node scheduling, node clustering, localization, data aggregation etc. Innovative use of swarm intelligence techniques in the above mentioned functional stages is the latest trend among researchers to improve network lifetime, coverage and connectivity, which is briefly explained in this survey. The popular SI techniques are largely applied to solve combinatorial problems in sensor networks because of its quick convergence, quality and optimized solution and simplicity. However most of the SI algorithms need large memory because of its iterative nature and hence such algorithms are restricted to the powerful nodes of the sensor network. This could be a key area for future research direction in this area. Also hybrid SI techniques are very less applied in WSN

Future research directions on SI in WSN are briefed below:

1) Hybrid SI techniques to target WSN issues.

2) Most of the algorithms are developed for stationary sensor network. Hence mobile sensor network could be encouraged further.

3) Existing SI techniques are mostly simulation based. Those could be applied for real time applications.

4) Cross-layer approach using SI techniques.

5) SI technique like bee colony optimization is less applied for node scheduling problem. This work could be taken in future.

6) More scope of ACO and BCO algorithms in WSN localization.

7) More scope of BCO algorithms in WSN data redundancy reduction.

An overview of WSN, its current issues, SI paradigms and SI based solutions for WSN problems are explained in this survey. In future, SI state-of-the-art algorithms can be applied to WSN applications to achieve better solutions than the existing and to improve the SI algorithms by adding extra features to focus real time applications.

References

[1] 1I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *ELSEVIER Computer Networks* , Vol.38, No.4(2002), pp.393-422.

[2] 2Q. Ling, Z. Tian, Y. Yin and Y. Li, "Localized structural health monitoring using energy-efficient wireless sensor networks," *IEEE Sensors Journal*, Vol.9, No.11(2009), pp.1596-1604.

[3] 3Melike Erol-Kantarci and Hussein T. Mouftah, "Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid," *Trans on Smart Grid*, Vol.2, No.2(2011), pp.314-325.

[4] 4V.C. Gungor and M.K. Korkmaz, "Wireless Link-Quality Estimation in Smart Grid Environments," *International Journal of Distributed Sensor Networks*, Vol.1(2012), pp.1-10.

[5] 5T. Takabatake, "Power Consumption on Topologies for a Sensor-based Home Network," *IAENG International Journal of Computer Science*, 39(3),(2012),

[6] 6P. Vijay Kumar and T.S. Siddarth, "A Prototype Parking System using Wireless Sensor Networks," *International Journal of Computer Communication and Information System*, Vol.2,No.1(2010), pp.276-280.

[7] 7Ping Wang, Yan Yan, Gui Yun Tian, Omar Bouzid, and Zhiguo Ding, "Investigation of Wireless Sensor Networks for Structural Health Monitoring," *Journal of Sensors*,(2012) pp.1-7.

[8] 8L. Liu, B. Hu and L. Li, "Energy conservation algorithms for maintaining coverage and connectivity in wireless sensor networks," *IET Communication*, (2010) pp.786800.

[9] 9V. Katiyar, N. Chand and S. Soni, "A Survey on Clustering Algorithms for Heterogeneous Wireless Sensor Networks," *International Journal on Advanced Networking and Applications*, Vol.2, No.4(2011) pp.745-754.

[10] 10L. Damuut and D. Gu, "A survey of deterministic vs. nondeterministic node placement schemes in wsns," *SENSORCOMM 2012, The Sixth International Conference on Sensor Technologies and Applications*,(2012), pp. 154-158.

[11] 11G. Han, H. Xu, T. Q. Duong, J. Jiang, and T. Hara, "Localization algorithms of wireless sensor networks: a survey," *Telecommunication Systems*, Vol.52, No.4(2013), pp.2419-2436.

[12] 12L. Wang and Y. Xiao, "A Survey of Energy-Efficient Scheduling Mechanisms in Sensor Networks," *Mobile Network Applications*, Vol.11, No.5(2006), pp.723-740.

[13] 13R. Annie Uthra, S. V. Kasmir Raja, "QoS Routing in Wireless Sensor Networks A Survey," *ACM Computing Surveys*, 45(1):9,(2012).

[14] 14E. Bonabeau, M. Dorigo, G. Theraulaz, *Swarm Intelligence: From Natural to Artificial Systems*, Oxford University Press, New York, USA, (1999).

[15] 15A. Engelbrecht, *Computational Intelligence: An Introduction*, second ed.,Wiley (2007).

[16] 16J. Kennedy, R.C. Eberhart, Y. Shi, *Swarm Intelligence*, Morgan Kaufman, San Francisco, USA, (2001).

[17] 17M. Saleem, G.A.D. Caro, M. Farooq, "Swarm intelligence based routing protocol for wireless sensor networks: survey and future directions," *Information Sciences* , Vol.181,(2011), pp.45974624.

[18] 18M. Dorigo and T. Stutzle, *Ant Colony Optimization*, MIT Press, (2004).

[19] 19X. Liu and D. He, "Ant colony optimization with greedy migration mechanism for node deployment in wireless sensor networks," *Journal of Network and Computer Applications*, Vol.39, (2014),pp. 310 -318.

[20] 20Blum C, Li X, "Swarm intelligence in optimization," *Swarm intelligence introduction and applications. Springer*, (2008) pp.58-62.

[21] 21D. Karaboga, "An Idea Based On Honey Bee Swarm for Numerical Optimization," *Technical Report TR06*, , Erciyes University, Engineering Faculty, Computer Engineering Department, (2005).

[22] 22D. Karaboga, B. Basturk, "A comparative study of artificial bee colony algorithm," *Applied Mathematics and Computation*, 214,(2009) pp.108-132.

[23] 23D. Karaboga, B. Gorkemli, C. Ozturk, N. Karaboga, "A comprehensive survey: artificial bee colony (ABC) algorithm and applications," *Artificial Intelligence Review*,(2012),pp.1-37.

[24] 24J. Kennedy and R. C. Eberhar, "Particle swarm optimization," *Proc. IEEE Int. Conf. Neural Networks*,vol.4, (1995), pp.1942-1948.

[25] 25O. Younis, M. Krunz and S. Ramasubramanian, "Node Clustering in Wireless Sensor Networks: Recent Developments and Deployment Challenges," *IEEE Network*, Vol.20, No.3(2006), pp.20-25.

[26] 26D. Li, W. Liu, and L. Cui, "EasiDesign: an improved ant colony algorithm for sensor deployment in real sensor network system," *IEEE Globecom*,(2010), pp.1-5.

[27] 27Xuxun, L, "Sensor Deployment of Wireless Sensor Networks Based on Ant Colony Optimization with Three Classes of Ant Transitions," *IEEE Communications Letters*, 16,(2012), pp.1604-1607.

[28] 28J. Xiao, S. Han, Y. Zhang, and G. Xu, "Hexagonal grid-based sensor deployment algorithm," *in Proc. Control Decision Conf.*,(2010), pp.4342-4346.

[29] 29Joon-Woo Lee, Byoung-Suk Choi, Ju-Jang Lee, "Energy-efficient coverage of wireless sensor networks using ant colony optimization with three types of pheromones," *IEEE Transactions on Industrial Informatics*,Vol.7, No.3(2011), pp.419-427.

[30] 30S. Mini, S. K. Udgata, and S. L. Sabat, “Sensor deployment in 3-D terrain using artificial bee colony algorithm,” *in Proc. Swarm, Evol. Memetic Comput.*,(2010), pp.424-431.

[31] 31S. Mini, S. K. Udgata, and S. L. Sabat,“Artificial bee colony based sensor deployment algorithm for target coverage problem in 3-D terrain,”*in Proc. Distrib. Comput. Internet Technol.*,(2011), pp. 313-324.

[32] 32S. Mini, Siba K. Udgata, and Samrat L. Sabat,”Sensor Deployment and Scheduling for Target Coverage Problem in Wireless Sensor Networks,”*IEEE Sensors Journal*,Vol.14, No.3, (2014).

[33] 33M. Chaudhary and A. K. Pujari,”Q-coverage problem in wireless sensor networks,”*in Proc. Int. Conf. Distrib. Comput. Netw.*, (2009), pp. 325330.

[34] 34C. Ozturk, D. Karaboga, and B. Gorkemli,”Probabilistic dynamic deployment of wireless sensor networks by artificial bee colony algorithm,”*Sensors*, Vol. 11, No. 6, (2011),pp. 60566065.

[35] 35H Du, Q Pan, Q Pan,Y Yao, Q Lv,”An improved Particle Swarm Optimization-Based Coverage control method for wireless sensor network,”*Advances in Swarm Intelligence Lecture Notes in Computer Science*, Vol.8795, (2014),, pp. 114-124.

[36] 36Li, Z.; Lei, L,”Sensor Node Deployment in Wireless Sensor Networks Based on Improved Particle Swarm Optimization,”*In Proceedings. IEEE International Conference on Applied Superconductivity and Electromagnetic Devices*, (2009), pp. 215-217.

[37] 37X. Wang, S. Wang, and J. J. Ma,”An improved co-evolutionary particle swarm optimization for wireless sensor networks with dynamic deployment,”*Sensors*,Vol.7, (2007), pp. 354370.

[38] 38. J. Li, K. Li, and W. Zhu, ”Improving sensing coverage of wireless sensor networks by employing mobile robots,”*in Proc. Int. Conf. Robot. Biomimetics*, (2007), pp. 899903.

[39] 39. W. Wang, B. Wang, Z. Liu, L. Guo and W. Xiong,”A cluster-based and tree-based power efficient data collection and aggregation protocol for wireless sensor networks,”*Information Technology Journal*,Vol.10, No.3, (2011), pp.557-564.

[40] 40. O.Boyinbode, H. Le, A. Mbogho, M. Takizawa, R. Poliah,"A Survey on Clustering Algorithms for Wireless Sensor Networks," *Proceedings of 2010 13th International Conference on Network-Based Information Systems*, (2010),pp. 358364.

[41] 41. M. Saleem, G.A. Di Caro, M. Farooq, "Swarm Intelligence based routing protocol for wireless sensor networks: Survey and future directions," *Information Sciences*,181(2010), pp. 45974624.

[42] 42. Vivek Katiyar., Narottam Chand. and Surender Soni, "A Survey on Clustering Algorithms for Heterogeneous Wireless Sensor Networks," *International Journal on Advanced Networking and Applications*, Vol. 02, No. 04, (2011), pp.745-754.

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

[44] 44. W. Heinzelman, A. Chandrakasan and H. Balakrishnan,"Energy-efficient Communication Protocol for Wireless Microsensor Networks," *33rd Hawaii Int. Conf. Syst. Sci.*,(2000).

[45] 45. W. B. Heinzelman, A. P. Chandrakasan, and H. Balakrishnan,"An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*,Vol.1, No. 4,(2002),pp. 660670.

[46] J.-Y. Kim, T. Sharma, B. Kumar, G. S. Tomar, K. Berry, and W.-H. Lee,"Inter cluster ant colony optimization algorithm for wireless sensor network in dense environment," *International Journal of Distributed Sensor Networks*,vol. 2014,

[47] 47. Salehpour, A.; Mirmobin, B.; Afzali-kusha, A;"An Energy Efficient Routing Protocol for Cluster-based Wireless Sensor Networks Using Ant Colony Optimization," *IEEE Proceedings of the 5th International Conference on Innovations in Information Technology*, (2008),pp. 455459.

[48] 48. Ziyadi, M.; Yasami, K.; Abolhassani, B."Adaptive Clustering for Energy Efficient Wireless Sensor Networks Based on ant Colony Optimization," *IEEE Proceedings of the 7th Annual Communication Networks and Services Research Conference*,(2009), pp. 330334.

[49] 49. Du, J.; Wang, L;"Uneven Clustering Routing Algorithm for Wireless Sensor Networks Based on Ant Colony Optimization," *Proceedings of the*

3rd IEEE International Conference on Computer Research and Development (2011), pp. 6771.

[50] 50. Karaboga D, Okdem S, Ozturk C,"Cluster based wireless sensor network routings using artificial bee colony algorithm,"*In: 2010 International conference on autonomous and intelligent systems (AIS)*, (2010), pp. 15.

[51] 51. D. Karaboga, S. Okdem, and C. Ozturk,"Cluster based wireless sensor network routing using artificial bee colony algorithm," *Wireless Netw.*, Vol. 18, No. 7, (2012),pp. 847860.

[52] 52. C. T. Cheng, C. K. Tse, and F. C. M. Lau,"A clustering algorithm for wireless sensor networks based on social insect colonies,"*IEEE Sensors J.*, Vol. 11, No. 3, (2011), pp. 711721.

[53] 53. N. M. A. Latiff, C. C. Tsimenidis, and B. S. Sharif, Energy-aware clustering for wireless sensor networks using particle swarm optimization,"*in Proc. 18th IEEE Int. Symp. Pers., Indoor Mobile Radio Commun.*, (2007), pp. 15.

[54] 54. X. Cao, H. Zhang, J. Shi, and G. Cui, "Cluster heads election analysis for multi-hop wireless sensor networks based on weighted graph and particle swarm optimization,"*in Proc. 4th Int. Conf. Natural Comput.*, Vol. 7, (2008),pp. 599603.

[55] 55. D.X. Han, R.H. Zhang, and D.H. Liu, "PSO-based energy-balanced double cluster-heads clustering routing for wireless sensor networks,"*Computer Engineering.*,Vol. 36, No. 10, (2010) pp. 100-102.

[56] 56. Singh, B., Lobiyal, D.K.,"Energy-aware cluster head selection using particle swarm optimization and analysis of packet retransmission in WSN,"*Procedia Technol.*, (2012), pp. 171176.

[57] 57. Crossbow.,"Power management and batteries, "*http://www.xbow.com/Support/appnotes.htm*, (2004).

[58] 58. A.C. Valera, W.-S. Soh, H.-P. Tan,"Survey on wakeup scheduling for environmentally-powered wireless sensor networks,"*Elsevier Comput Commun*, 52, (2014), pp. 2136.

[59] 59. Cheng, C.-T.; Tse, C.K.; Lau, F.C.M, "A Bio-Inspired Scheduling Scheme for Wireless Sensor Networks,"*Proceedings VTC Spring*, (2008), pp. 223227.

[60] 60. Joon-Woo Lee and Ju-Jang Lee,"Ant-Colony-Based Scheduling Algorithm for Energy-Efficient Coverage of WSN," *IEEE Sensors Journal*,Vol. 12, No. 10, (2012), pp.3036-3046.

[61] 61. Y. Lin, X. Hu, and J. Zhang, "An ant-colony-system-based activity scheduling method for the lifetime maximization of heterogeneous wireless sensor networks," *in Proc. 12th Annu. Conf. Genetic Evol. Comput.*, (2010), pp. 2330.

[62] 62. Chaolong Yu , Wenzhong Guo ; Guolong Chen,"Energy-balanced Sleep Scheduling Based on Particle Swarm Optimization in Wireless Sensor Network," *IEEE Parallel and Distributed Processing Symposium*, (2012), pp. 1249 1255.

[63] 63. L. Dong, H. Tao, W. Doherty, and M. Young,"A Sleep Scheduling Mechanism with PSO Collaborative Evolution for Wireless Sensor Networks," *International Journal of Distributed Sensor Networks*,(2015), Article ID 517250.

[64] 64. J. Mao, Z. Wu, and X. Wu,"A TDMA scheduling scheme for many-to-one communications in wireless sensor networks," *Comput. Commun.*,vol. 30, no. 4,(2007), pp. 863872.

[65] 65. Lavanya, D.; Udgata, S.K,"Swarm intelligence based localization in wireless sensor networks," *Lect. Notes Comput. Sci.*, 7080,(2011), pp. 317328.

[66] G. Mao, B. Fidan, and B. Anderson,"Wireless sensor network localization techniques," *Computer Networks*,Vol.51, No.10, (2007), pp. 2529-2553.

[67] F. Qin, C. Wei, and L. Kezhong,"Node Localization with a Mobile Beacon Based on Ant Colony Algorithm in Wireless Sensor Networks," *In Proc. of Int. Conf. on Communications and Mobile Computing*, (2010), pp. 303-307.

[68] 68. A. Moussa, N. El-Sheimy,"Localization of wireless sensor network using bees optimization algorithm," *in: Proceedings of IEEE International Symposium on Signal Processing and Information Technology*,(2010),pp. 478481.

[69] 69. A. Gopakumar and L. Jacob,"Localization in wireless sensor networks using particle swarm optimization," *in Proc. IET Int. Conf. Wireless, Mobile Multimedia Netw.*,(2008), pp. 227230.

[70] 70. R. V. Kulkarni, G. Venayagamoorthy, and M. X. Cheng, "Bio-inspired node localization in wireless sensor networks," *in Proc. IEEE Int. Conf. Syst., Man Cybernetics*, (2009).

[71] 71. M. Ramesh, P. Divya, R. Kulkarni and R. Manoj, "A swarm intelligence based distributed localization technique for wireless sensor network," *ACM ICACCI'12*, (2012).

[72] 72. R. Rajagopalan and P. K. Varshney,"Data-aggregation techniques in sensor networks: A survey," *IEEE Commun. Survey. Tutorials*, Vol. 8, No. 4, (2006), pp. 4863.

[73] 73. S. Lindsey, C.S. Raghavendra,"PEGASIS: Power-efficient gathering in sensor information systems," *in: IEEE Aerospace Conference Proceedings*, (2002), pp. 11251130.

[74] 74. Maraiya, K., Kant, K., Gupta, N, "Wireless sensor network: a review on data aggregation," *International Journal of Scientific and Engineering Research*, 2(4), (2011),pp.1-7.

[75] 75. S. Roy, M. Conti, S. Setia, S. Jajodia,"Secure data aggregation in wireless sensor networks," *IEEE Trans. Inf. Forensics Secur.*, 7 (3),(2012), pp.10401052.

[76] 76. R. Misra, C. Mandal,"Ant-aggregation: ant colony algorithm for optimal data aggregation in wireless sensor networks," *in: Proceedings of IEEE International Conference on Wireless and Optical Communications Networks*, (2006).

[77] 77. W.-H. Liao, Y. Kao, C.-M. Fan, "Data aggregation in wireless sensor networks using ant colony algorithm," *Journal of Network and Computer Applications*, 31 (4),(2008), pp. 387401.

[78] 78. C. Lin, G. Wu, F. Xia, M. Li, L. Yao, Z. Pei,"Energy efficient ant colony algorithms for data aggregation in wireless sensor networks," *J. Comput. System Sci.*,78 (6), (2012),pp. 16861702.

[79] 79. Y. Lua, J. Chen, I. Comsa, P. Kuonen, B. Hirsbrunner,"Construction of data aggregation tree for multi-objectives in wireless sensor networks through jump particle swarm optimization," *Procedia Computer Science*, Vol.35, (2014), pp. 7382.

[80] 80. M. A. Bharathi, B. P. Vijayakumar, and D. H. Manjaiah, "Cluster based data aggregation in WSN using swarm optimization technique," *International Journal of Engineering and Innovative Technology (IJEIT)*, Vol. 2, No. 12,(2013).

[81] 81. M. A. Bharathi, B. P. Vijayakumar, and M. Mallikarjuna,"A novel approach for energy efficient data aggregation using elephant behaviour as swarm intelligence," *Lecture Notes on Software Engineering*, Vol. 1, No. 2, (2013), pp. 153155.

[82] 82. Bhuyan, B., Sarma, H., Sarma, N., Kar, A., Mall, R "Quality of Service (QoS) Provisions in Wireless Sensor Networks and Related Challenges," *Wireless Sensor Network 2*,(2010),pp.861868

[83] 83. Li Z. and Shi Q.,"An QoS algorithm based on ACO for wireless sensor network," *HPCC 2013 and EUC 2013*, (2014), pp. 1671-1674.

[84] 84. S. Kumar, M. Dave, S. Dahiya,"ACO Based QoS Aware Routing for Wireless Sensor Networks with Heterogeneous Nodes," *Emerging Trends in Computing and Communication Lecture Notes in Electrical Engineering*, Vol.298, (2014), pp 157-168.

[85] 85. L. Cobo, A. Quintero, S. Pierre, "Ant-based routing for wireless multimedia sensor networks using multiple QoS metrics," *Computer Networks*, 54,(2010), pp. 29913010.

[86] Xi-huang Zhang, Wen-bo Xu,"QoS based routing in wireless sensor network with particle swarm optimization," *Xi-huang Zhang, Wen-bo Xu, QoS based routing in wireless sensor network with particle swarm optimization, Proceedings of the 9th Pacific Rim international conference on Agent Computing and Multi-Agent Systems*, (2006).

[87] 87. Xi-Hong C, Shao-Wei L, Jiao G, Qiang L. "Study on QoS multicast routing based on ACO-PSO algorithm," *In: Proceedings of 2010 international conference on intelligent computation technology and automation*, (2010),pp. 534537.

[88] 88. Patel, M.K., Kabat, M.R., Tripathy, C.R."A Swarm Intelligence Based Algorithm for QoS Multicast Routing Problem," *Lecture Notes in Computer Science Volume 7077*, (2011),pp 38-45.

[89] 89. Patel MK, Kabat MR, Tripathy CR, "A hybrid aco/pso based algorithm for qos multicast routing problem," *Ain Shams Eng J.*,5(1),(2014), pp.113120.

[90] 90. G. Han, H. Xu, T. Duong, J. Jiang, and T. Hara, "Localization algorithms of wireless sensor networks: A survey," *Telecommun. Syst.*, Vol. 52, No. 4,(2011),pp. 118.

[91] 91. Nazir, U., Arshad, M. A., Shahid, N., Raza, S. H. ," Classification of localization algorithms for wireless sensor network: A survey," *In Open source systems and technologies (ICOSST)*, (2012), pp. 15,

[92] 92. N. Shigei, H. Miyajima, and H. Morishita,"Energy Consumption Reduction of Clustering Communication Based on Number of Neighbors for Wireless Sensor Networks," *IAENG International Journal of Computer Science*, 37(3),2010.