1. Introduction

The wireless sensor network can be defined as a distributed network system of various embedded sensor nodes and usually a single sink node over a monitoring region (Akyildiz et al. 2002). Sink node works as supervisor to all dominating sensor nodes. Each node is consisting of communication, processing and data storage unit as well as a power storage system. Sensor node having the capability to process a limited amount of data with the help of a tiny processor and it has the capability to transmit and receive a limited amount of data to neighbouring nodes or sink node. It also consists of a limited amount of data storage and independent battery storage to make the node alive. Sink node works as a supervisory node and transmit data to dominant nodes and also receive data from them. Now depending upon the purpose those sensor nodes read data through tiny sensors from the environment and those data after processing by a tiny processor of sensor nodes transmitted to the sink node. The sink node analyses those data and controls those sensor nodes by propagating instructions. This network system works through a multi-hop communication system (El-Hoiydi and Decotignie 2004). Nowadays this type of network is being used in a modern army, environmental monitoring, battlefield monitoring, body area network, intelligent household etc.

Efficient data transmission or data routing is a challenging task due to a huge number of use of sensors and their haphazard arrangement without any planning. In our approach, we have deployed the sensor nodes after well-organized planning for the arrangement of WSN nodes so that efficient data transmission can be achieved. Generally, many sensor nodes are deployed in the supervising area to form a robust wireless network. Now the proper use of those sensors may give a better route so that the energy required to transmit and receive a signal during the data transmission can be minimized. In case of sensor deployment to develop a WSN we generally select/choose an area to deploy the sensors participating in the network and in our approach, the entire area has been divided into so many uniform hexagonal cells. Each cell consists of so many sensor nodes. The sink node acts as an access point of the server node. The main aim of routing is to transfer information from one node of a particular cell to another node of an adjacent cell so that, the total power consumption or cost for that particular route is minimized.

Network-clustering method in WSN, the entire network is clustered into a small network cell generally called cluster (Gupta et al. 2005). In a cluster one active node is considered as cluster head (CH). Here active-node denotes the node which is taking an active part in the data communication as well as sensing environment. In the concept of duty cycle, one node is considered as an active or awake node and other nodes as a sleeping node. The active node takes participation in data communication and the sleep node becomes inactive. This cycle of sleep and active mode is called duty cycle (Geisberger 2008). In this paper, we have considered duty cycle inside the cluster where cluster head is considered as active node and other nodes present in the cluster is considered as sleep node for a particular data-communication path (see figure 5). In the data communication phase, the data is communicated between a sink node (SN) to cluster head (CH) or one cluster head (CH) to another cluster head (CH) and during this communication the energy of participating cluster head and sink node is consumed (see equation no 5,6 and 7). Now the selection of cluster head and establishment of an efficient path to minimize the energy consumption is the main objective of our paper. After establishing the efficient path by the help of the ACO algorithm we can design an efficient network. Now minimization of energy consumption can be applied to the network and ultimately with the help of DE-QPSO hybrid algorithm maximizing the coverage area we can be measured so that we can justify the minimization of energy consumption with respect to maximization of area coverage. Here the cluster head is responsible to collect information by sensing the environment of a particular cluster and send it to either adjacent cluster head (in case of CH-CH communication) or to the sink node (in case of CH-CH communication). This method is used to improve network durability, robustness and scalability of the network.

There are two types of communication and those are, Inter-cluster communication and intra-cluster communication. Inter-cluster communication and intra-cluster communication plays a very important role in data routing. In the case of Inter-cluster communication, the communication is limited to the cluster itself and in the case of inter-cluster communication, the communication is done between two or more clusters.

In our approach, we have mainly concentrate the communication type as inter-cluster communication as because our main goal is to cover the maximum area without consuming much more energy. For efficient network, network-dedicated routing protocols (Wang 2006) may be required and in our approach the have used ACO algorithm to select cluster head position.. As we have used the sleep-awake method to make our network alive for a long time it is required to elect new cluster head node after every round.

In this paper we have worked with the following characteristics to make a network reliable should have:

i) WSN mainly consist of a processing unit, a communication unit, power backup unit and sensing the unit, where the power backup unit is responsible to supply power to all other units to work properly but due to the tiny size of WSN nodes, the power backup is limited and it makes the nodes unreliable after continuous use of those nodes. That means after the full discharge of the backup unit the system become unreliable. Now if, the minimization of power consumption can be carried out successfully then the system may achieve better sustainability to get a reliable sensor network system. Minimization of power consumption also leads to minimization of variable cost.

ii) The coverage of a WSN is determined by considering the area covered by its sensor node in the 3D space. The goal is to maximize the coverage space, in order to transmit data up to a maximum range. In this case, the optimization problem faces the constraint that, in order to magnify the signal strength to cover the maximum space, the energy efficiency decreases exponentially, while the energy supply to a simple sensor node is limited. On the other hand, increasing the power supply makes the network unreliable, because if the power consumption is high, the duration of sustainability of those nodes will decrease. Thus, the optimal reliability for the WSN, which is most important for any sustainable WSN within its duty time, it cannot be achieved. Therefore, the coverage space must be optimized with respect to those constraints, which affect the energy consumption rate.

2. Related Work

We know that A wireless sensor network (WSN) consists of sensor nodes and they are distributed around a given location. These sensors have limited energy capacity to be active for a long period of time (Pantazis et al. 2013). For the last few years, sensors have improved in their computational capabilities; the batteries are still not highly efficient in comparison. Consequently, to extend the life of a sensor node, research has been pointed towards reducing the demand for energy of the nodes. The reason for doing this, to design the core aspects in a WSN are Energy Efficiency and Reliability (Zenia et al. 2016). By using Energy Efficient (EE) Routing, the life of a sensor node can be extended (ECE 2013). During transmission energy is expended, the most energy efficient route during transmission will consume the least energy.

Basically, routing protocols for WSN are classified into the flat protocol, hierarchical protocol and location-based Protocol (Liao and Zhu 2013). In Flat protocol routing scheme, distribution of the nodes is uniform. In the case of the hierarchical scheme, nodes are given different roles and groups known as clusters (Gajjar 2015). In the case of location-based protocol, each cluster must have a Cluster Head (CH). The cluster head is a node that has higher capabilities than other nodes and is used to relay data to the sink node. Within a distribution of nodes, there may be many possible routes to get to a particular destination. In our approach, we have used this type of protocol to achieve efficient network.

Mathematical models were developed in (Lee and Moon 2014) to determine the most energy efficient route to use in a WSN under resource restriction. The task of determining the most energy efficient route is a hard optimization problem (Wang et al. 2008). Consequently, many meta-heuristic techniques have been developed to find the most optimal energy efficient route.

Liao and Zhu 2013 presented the primary objectives of the wireless sensor network routing protocol design. The main purpose of this protocol is to balance network energy consumption and to improve the efficiency of data transmission. Therefore it will extend the lifetime of the entire network. The paper analyses the usefulness of LEACH protocol in the cluster-head selection, and proposes an enhanced clustering algorithm. This new algorithm takes the node's remaining energy and location information into account optimizes the selection method of the threshold for electing cluster-head improves optimal cluster-head selection approach that is normal nodes select the optimal cluster-head based on the cost function.

An Adaptive Ant Colony Optimization (ACO) algorithm is proposed in (Ye and Mohamadian 2014) for clustering based dynamic routing in a WSN. This was designed to deal with the impulsive nature of a Wireless Sensor Network. Sensors nodes can be deployed in two different types, sparse or dense nature. The ACO finds the optimal network setting to improve data aggregation so that data redundancy can be reduced. An adaptive routing scheme based on ACO was also developed in (Wang et al. 2008). Route selection is based on the residue energy in the nodes as well as the location of nodes. In this case, clusters were not used in the grouping of nodes. Fuzzy logic was used in addition to ACO in (Gajjar et al. 2015) in a cross-layer WSN protocol stack to optimize routing in a WSN. To improve the Energy Efficiency of the routing protocol, a multilayer approach was adopted. Nodes were grouped into clusters with cluster heads which are closest to the sink. Fuzzy logic was used in the cluster head selection using metrics such as residual energy, number of neighbours and superiority of communication link for the selection. However, ACO was used for reliable and energy efficient inter-cluster routing from cluster heads to sinks. ACO was further used to determine a multi-objective optimization i.e. energy efficiency and security of transmitted data (Luo et al. 2015) in a WSN. The factors used to carry out this include the time delay, bandwidth and energy consumption. Neural Network was used together with ACO for the purpose of routing in (Li et al. 2015). The neural network is used to select the cluster head while ACO was used to determine the best route. An ACO was used to develop an enhanced routing protocol for WSN (Umadevi and Devapriya 2015) with mobility as the metric.

Artificial Bee Colony meta-heuristics algorithm (Ari et al. 2016) and improved harmony search algorithm (Zeng and Dong 2016) were used to determine the optimal energy efficient route in a WSN. An Improved Genetic Algorithm was developed to eliminate the possibility of choosing an invalid note for routing in a WSN (Yao 2016). Parameters used in the node selection include nodes position in relation to sink, neighbouring nodes, remaining energy and energy requirement. Since this research work was based on using Firefly and Ant Colony optimization algorithms for route optimization, the literature will be based on them.

3. Methodology

In this paper two modified meta-heuristic algorithms have been used, i.e., modified ACO algorithm for selecting the cluster head of the efficient WSN and hybrid DE-QPSO algorithm to maximize the total coverage area of the network.

In Ant Colony Optimization, we select an efficient route by applying the optimization techniques keeping mind the constraints. In this case, we have to cover the target area efficiently subject to fulfilling the condition of constraints (see equation 7A to 7J). After the temporary route is established, each and every route loses some energy due to the transmission and receiving data. When, Energy level comes below the threshold value then the route is broken and we have to detect where the route is broken. The Solution to establish a new Route is found out taking help of nearest adjacent sensor node which was in sleeping condition. Now, the sleeping node will be alive and the previous node will be declared as a dead node. This process will be continued until each and every node is being used and is declared as a dead node. Depending upon the previous condition the lifetime of the entire WSN in fixed. By following this process we have been able to establish a new protocol for WSN to minimize the power consumption and maximize the coverage area.

Box 1. Pseudo-code for ACO

Step 1: Using randomness property at first generates the $ANT_{population}$ (*population variant*) (related to population set generation) and evaluate the $ANT_{solution}$ and fix the ANT_{size} (*population size variant*). Define Attractiveness (τ) and Visibility Function (η). Set the bounds of decision variables.

Step 2: Set the iteration (generation) number $t = 0$.

Step 3: Initialize randomly the $ANT_{solution}$ of the population $ANT_{population}(t) = \{p_i(t);\ i=1,\ldots, ANT_{size}\}$.

Step 4: Calculate the next $ANT_{solution}$ using the Attractiveness function (τ) and Visibility Function (η). In this paper, ere Visibility function is matched/correlated with fitness function [$fitness(p_i)$] for each variable p_i of $ANT_{population}(t)$ and attractiveness is related to the local Pheromone-updating phenomenon.

Step 5: Search the global-best $ANT_{solution}$ (i.e., $ANT_{population}(global)$) having the best fitness/Visibility rate depending upon global-Pheromone updating law and local updating law and choose best solution.

Step 6: Repeat step 1 to 5 until termination criterion is met and increase generation by 1 i.e.,

$t = t+1$, which is related to time.

Step 7: Check the termination-criterion. If termination criteria are not met, go back to Step 6, otherwise go to Step 8.

Step 8: Print the value of fitness and/or Attractiveness value of $ANT_{population}(global)$.

Step 9: End.

Reliability Optimization through minimizing consumed energy and Maximum Coverage area optimization Model

In one word the reliability of a system can be defined as “probability of sustainability”. Here sustainability denotes the durability of the system in its proper working condition. In this paper our approach aiming for reliability improvement with respect to minimization of energy consumption and maximization of coverage area with the help of two meta-heuristic algorithms. Firstly we have used the ACO algorithm to detect a feasible path of communication in WSN network to minimize the energy consumption during data communication. Secondly, we have used a meta-heuristic algorithm namely DE-QPSO algorithm to maximize the coverage area of the target area.

The coverage optimization problem is one of the basic problems in WSN that means the reliability of the network can be increased if the range of coverage of WSN can be maximized. If sensor node can cover more area or 3D space that means with the help of less number of sensor node more equivalent area of the monitoring region can be covered and energy can be saved and the sustainably of the network can be increased. To optimize the “coverage area” if we increase the signal strength of the network to cover maximum area there are some limitations (constraints). The limitations are energy storing capacity of a sensor node is limited and the network may be unreliable (Miao 2009) due to the increase of power supply to the network. Therefore the area coverage should be optimized with subject to the correlated constraints otherwise reliability of the WSN can’t be achieved.

Here we are going to describe the participating meta-heuristic algorithms i.e., DE, QPSO then hybrid DE-QPSO.

Differential Evolution (DE)

At first, the differential evolution algorithm is suggested by Storn and Price (2006). Those researchers have realized that in real life there are many problems are present which are non-differential, non-linear, and discrete in nature and the objective function having many local minima with subject to related constraints. Now those problems can’t be solved analytically and due to the stochastic nature of this algorithm, this algorithm provides an approximate solution for those problems. This algorithm is a population-based algorithm. In this algorithm, we use the difference between randomly selected individuals (vectors). The vector which is the in the feasible solution set of the desired result is called the target vector. A trial solution is generated by combining the weighted difference between the current vector and the target vector.

This above-mentioned procedure is referred to as the mutation operation. After the mutation operation, the recombination (or crossover) operation is applied to produce a better offspring.

Better offspring is selected depending upon the fitness function of the objective function. The fitness function of offspring is compared with the fitness function of parent and if the fitness function of newly produced offspring is found better, it is accepted otherwise rejected. So in this phase mainly the value of fitness function is improved. The value of the donor vector has computed this phase. The value of the donor vector is the combination of the weighted difference of the first two individuals (vectors) to the third individual (vector).

Quantum behaved Particle Swarm Optimization (QPSO)

At first the mechanism of Quantum PSO (QPSO) was developed by Sun et al. (2004). This mechanism is also a PSO variant which consist almost all characteristics of PSO with added features of quantum mechanism. Therefore it may be written, in case of QPSO the particle movement follows quantum behaviour rather a Newtonian approach and the quantum behaviour of a particle can be defined by the laws of quantum mechanics and this mechanism can be defined by Schrödinger equation.

The equation is as follows:

$$\mathrm{j}\hbar \frac{\partial}{\partial \mathrm{t}} \Psi(\mathrm{r},\mathrm{t}) = \mathrm{H}(\mathrm{r})\Psi(\mathrm{r},\mathrm{t}), \tag{1}$$

where,

$$\mathrm{H}(\mathrm{r}) = -\frac{\hbar^2}{2\mathrm{m}}\nabla^2 + V(r), \tag{2}$$

H(r) is a time-dependent Hamiltonian operator; $\hbar$ is the Planck's constant; m is the mass of the particle; and $\mathrm{V(r)}$ is a potential-energy-distribution function. The amplitude i.e., $\mathrm{Q} = |\Psi|^2$, of the wave function $\Psi(\mathrm{r},\mathrm{t})$ in equation (1). It is a probability for the movement of the particle, under the normalization as described in equation 3:

$$\iiint |\Psi(\mathrm{r},\mathrm{t})|^2 dxdydz = 1.0 \tag{3}$$

In QPSO, the swarm is considered as a quantum system where each particle has a quantum state based on the employed wave function,

$$p_j = \frac{\varphi_1 p_{ij} + \varphi_2 p_{gj}}{\varphi_1 + \varphi_2}, \quad j = 1, 2, ...n \tag{4}$$

the position, p of a particle, x_i, is defined as the weighted mean of its best position, p_i, and the overall best position of the swarm, p_g, where $\varphi_1 = c_1 r_1$ and $\varphi_2 = c_2 r_2$, with c_1, c_2 being the cognitive and social parameter of PSO, respectively, and r_1, r_2, being uniformly distributed random numbers in [0,1].

The Proposed hybrid DE-QPSO algorithm

In this paper a Meta-heuristic the hybrid stochastic approach has been considered as optimization algorithm to solve the problem of coverage model of WSN. Hybridization has occurred between two well-known stochastic optimization techniques namely Differential Evolution (DE) and Quantum behaved Particle Swarm Optimization (QPSO).

The steps of the proposed meta-heuristic hybrid algorithm (Sahoo 2014), i.e. the DE-QPSO, are given below (See also figure 1).

Step-1: Set total population size (2*$Population$), 50% population assigned for DE i.e. $Population_{\mathrm{DE}}$, and the rest of 50% population assigned for PSO i.e. $Population_{\mathrm{QPSO}}$, maximum number of generations (*Max_generation*), probability of crossover ($Probability_{crossover}$), probability of mutation ($Probability_{mutation}$) and the bounds of decision variables.

Step-2: Set i=0. [i represents the generation/iteration number].

Step-3: Initialize the chromosomes/particles of the population

$Population_{DE}$(j) = {x_j(i); j=1,…,Number of Population(NP)} and P_{QPSO}(j) = {x_j(i); j=NP+1,…,2·NP}..

Step-4: Compute the fitness function $f(x_j)$ for each chromosome xi of $Population_{\mathrm{DE}}$(i) and each particle x_i of $Population_{QPSO}(i)$.

Step-5: Find the global best chromosome/particle ($Population_{global}$) having the best fitness value.

Step-6: Divide the chromosomes/particles into two groups, viz. $Population_{DE}(i)$ and $Population_{QPSO}(i)$ with equal population size.

Step-7: Repeat the following until the termination criterion is satisfied:

Step 7.1 Increase the value of i by unity.

Step 7.2 Apply DE algorithm for 50% of the population i.e., $Population_{DE}(i)$.

Step 7.2.1 Apply the operator for mutation to compute the donor vector for different DE strategies.

Step 7.2.2 Apply operator for recombination/crossover to obtain trial vector from the target vector and the donor vector.

Step 7.2.3 Using tournament selection method upgrade the population of the next generation $Population_{DE}(i)$ from the previous population $Population_{DE}(i-1)$. from generation (i-1).

Step 7.3 Regenerate populations for QPSO by the best 50% of population replacing the worst 50% of population.Apply QPSO for $Population_{QPSO}(i)$.

Step 7.3.1 Improve the best position of each particle by comparing the position of all chromosomes of $Population_{DE}(i)$.

Step 7.3.2 Obtain the new position of each particle.

Step 7.3.3 Improve the position of each particle and also find the global best particle ($Population_{global}$).

Step-8: Print the position and fitness of global best particle.

Step-9: End.

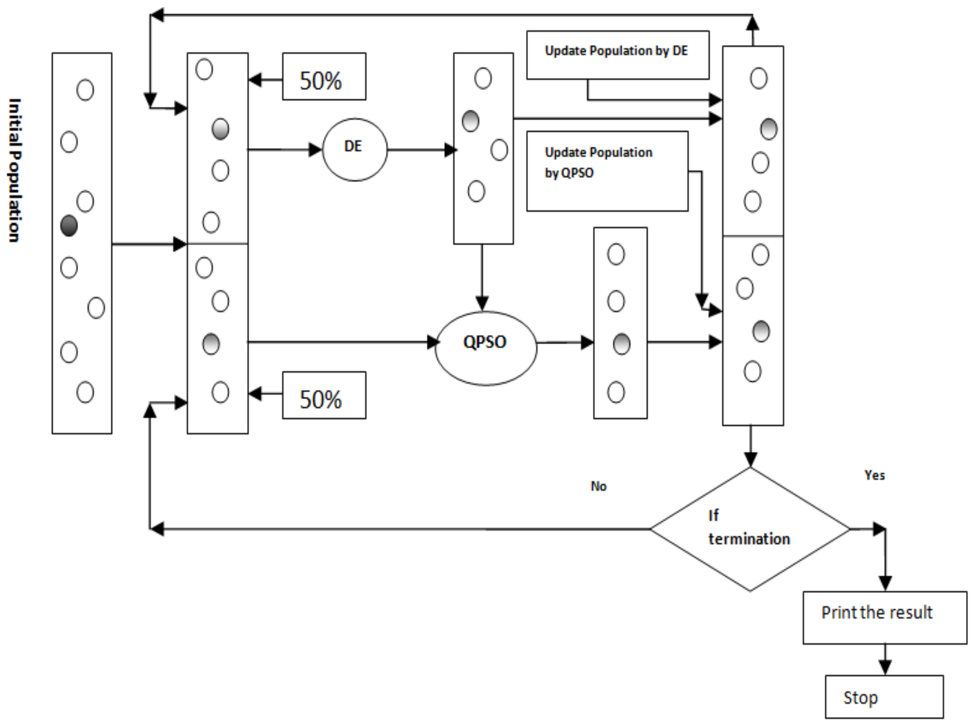

Figure 1. Block Diagram of the hybrid DE-QPSO algorithm.

4. Solution Methodology:

In this paper we have some steps through which the entire process of construction of the network can be defined.

1. **Indexing of nodes**: It is a process through which each and every sensor node is being denoted with the help of a sequential number. After the deployment of the nodes, again an indexing is done with the help of row and column number of the cell (as depicted in the figure 2.) The indexing of a cluster cell has been represented using row index and column index present in the cluster cell structure in the network.

2. **Clustering:** Here clustering means dividing target area into some uniform blocks. Here our aim is to construct the efficient cluster cell. The target area of WSN has been clustered using efficient cluster cell. The structure of cluster cells have been chosen as hexagonal as because it has been proved (Katz 2008) that using hexagonal cluster cell the target area can be

covered efficiently. Here the term efficiently refers to the efficient and uniform coverage of target area with no gap between the neighbouring clusters.

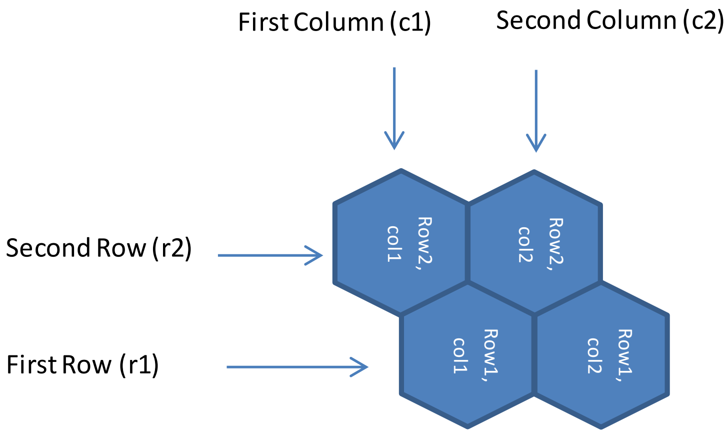

Figure 2. structure of cluster cell and their representation

3. Positioning of cluster ~~head~~ node to the cluster cell: This positioning method refers to the deployment of sensor nodes and arrangement of those nodes maintaining a special pattern so that there is no space uncovered for observation during the data transmission between two nodes. Here cluster refers to the active node participating in the data communication. Here we have chosen hexagonal cell structure because it can be proved that if the arrangements of nodes maintain a hexagonal pattern the network can efficiently cover more space than that of other shapes like triangle, square. In comparison to circular pattern the hexagonal pattern is much more efficient because in case of circular pattern there will be some space uncovered in the contact point of adjacent circles. Therefore the cell arrangement is suggested as shown in the Figure 2.

4. **Deployment of WSN nodes** (different strategies):

A. **Random deployment**: randomly the certain numbers of nodes are deployed in the target area in a fixed amount of time and maintain a time interval but, without maintaining any fix strategy.

B. **S pattern deployment**: certain numbers of nodes are deployed in the target area in a fixed amount of time and maintaining a time interval. The path of deployment ship is following S pattern. Here the login and logout time of entry and exit to the deployment area should be fixed. In this paper we have calculated the energy consumption for this type of deployment only (see equation no 5 to 7).

C. **Spiral deployment**: certain numbers of nodes are deployed in the target area in a fixed amount of time and maintaining a time interval. The path of deployment ship is following spiral pattern. Here the login and logout time of entry and exit to the deployment area should be fixed.

5. **Choosing of nodes as cluster head:** Selection of a sensor node as cluster head: The selection of a sensor node as a cluster head (CH) is an important job towards development of an efficient network configuration. Here in this paper the selection of cluster head has been

done by calculating the uniform distance between different nodes in a cluster maintaining the following constraints.

a) One cluster head has been selected from one cluster for a single instance of transmission.

b) Due to data transmission, after energy consumption to a certain limit the cluster head position is changed and new cluster head.

6. **WSN network configuration through modified ACO algorithm:**

Using ACO algorithm choosing the optimized path for the minimization of energy consumption for transmitting the data as well as receiving data: ACO algorithm is used to choose the optimized the path for the minimization of energy consumption for transmitting the data. The linear problem as described below:

The energy consumption during successful data transmission between cluster head (CH) to cluster head (CH) and cluster head (CH) to sink node (SN) has been calculated and minimized using the below-maintained equations:

$$f(k,d) = Minimization\left(E^{Total}_{transmission}(k,d)\right) \tag{5}$$

Subject to,

$d \leq d_o$, for free-space propagation model and $d > d_o$ for two- ray ground propagation model.

Where d_o is the threshold transmission distance.

Where,

$$E^{Total}_{transmission}(k,d) = E^{Total}_{tx}(k,d) + E^{Total}_{rx}(k) \tag{5A}$$

$$E^{Total}_{tx}(k,d) = E^{SN-CH}_{tx}(k,d) + E^{CH-CH}_{tx}(k,d) \tag{5B}$$

$$E^{Total}_{rx}(k) = E^{SN-CH}_{rx}(k) + E^{CH-CH}_{rx}(k) \tag{5C}$$

For two- ray ground Propagation model

$$E^{SN-CH}_{tx}(k,d) = E^{SN-CH}_{Electronic-energy}(k) + E^{SN-CH}_{Amplifier}(k,d) \tag{5D}$$

$$E^{CH-CH}_{tx}(k,d) = E^{CH-CH}_{Electronic-energy}(k) + E^{CH-CH}_{Amplifier}(k,d) \tag{5E}$$

$$E^{SN-CH}_{rx}(k) = E^{SN-CH}_{Electronic-energy}(k) * k \tag{5F}$$

$$E^{CH-CH}_{rx}(k) = E^{CH-CH}_{Electronic-energy}(k) * k \tag{5H}$$

Therefore the problem can be defined as objective function as follows

$f(k,d) = Minimization\left(E_{transmission}^{Total}(k,d)\right)$ subject to, $d > d_o$ Where d_o is the threshold transmission distance. (6)

where, $E_{transmission}^{Total}(k,d) = E_{tx}^{Total}(k,d) + E_{rx}^{Total}(k)$ (6A)

$$E_{tx}^{Total}(k,d) = E_{tx}^{SN-CH}(k,d) + E_{tx}^{CH-CH}(k,d) \tag{6B}$$

$$E_{tx}^{SN-CH}(k,d) = E_{Electronic-energy}^{SN-CH}(k) + E_{Amplifier}^{SN-CH}(k,d) \tag{6C}$$

$$E_{tx}^{CH-CH}(k,d) = E_{Electronic-energy}^{CH-CH}(k) + E_{Amplifier}^{CH-CH}(k,d) \tag{6D}$$

$$E_{rx}^{Total}(k) = E_{rx}^{SN-CH}(k) + E_{rx}^{CH-CH}(k) \tag{6E}$$

$$E_{rx}^{SN-CH}(k) = E_{Electronic-energy}^{SN-CH}(k) * k \tag{6F}$$

$$E_{rx}^{CH-CH}(k) = E_{Electronic-energy}^{CH-CH}(k) * k \tag{6G}$$

For Free-space propagation model

$$E_{tx}^{SN-CH}(k,d) = E_{Electronic-energy}^{SN-CH}(k) * k + E_{Amplifier}^{SN-CH}(k,d) * k \tag{6H}$$

$$E_{tx}^{CH-CH}(k,d) = E_{Electronic-energy}^{CH-CH}(k) * k + E_{Amplifier}^{CH-CH}(k,d) * k \tag{6I}$$

$$E_{rx}^{SN-CH}(k) = E_{Electronic-energy}^{SN-CH}(k) * k \tag{6J}$$

$$E_{rx}^{CH-CH}(k) = E_{Electronic-energy}^{CH-CH}(k) * k \tag{6K}$$

$$E_{Amplifier}^{SN-CH}(k,d) = E_{fs}^{SN-CH} * d^2 \tag{6L}$$

$$E_{Amplifier}^{CH-CH}(k,d) = E_{fs}^{CH-CH} * d^2 \tag{6M}$$

Therefore the problem can be defined as objective function as follows

$f(k,d) = Minimization\left(E_{transmission}^{Total}(k,d)\right)$ subject to, $d <= d_o$ Where d_o is the threshold transmission distance. (7)

where, $E_{transmission}^{Total}(k,d) = E_{tx}^{Total}(k,d) + E_{rx}^{Total}(k)$ (7A)

$$E_{tx}^{Total}(k,d) = E_{tx}^{SN-CH}(k,d) + E_{tx}^{CH-CH}(k,d) \tag{7B}$$

$$E_{rx}^{Total}(k) = E_{rx}^{SN-CH}(k) + E_{rx}^{CH-CH}(k) \tag{7C}$$

$$E_{tx}^{SN-CH}(k,d) = E_{Electronic-energy}^{SN-CH}(k) * k + E_{Amplifier}^{SN-CH}(k,d) * k \tag{7D}$$

$$E_{tx}^{CH-CH}(k,d) = E_{Electronic-energy}^{CH-CH}(k) * k + E_{Amplifier}^{CH-CH}(k,d) * k \tag{7E}$$

$$E_{rx}^{Total}(k) = E_{rx}^{SN-CH}(k) + E_{rx}^{CH-CH}(k) \tag{7F}$$

$$E_{rx}^{SN-CH}(k) = E_{Electronic-energy}^{SN-CH}(k) * k \tag{7G}$$

$$E_{rx}^{CH-CH}(k) = E_{Electronic-energy}^{CH-CH}(k) * k \tag{7H}$$

$$E_{Amplifier}^{SN-CH}(k,d) = E_{fs}^{SN-CH} * d^2 \tag{7I}$$

$$E_{Amplifier}^{CH-CH}(k,d) = E_{fs}^{CH-CH} * d^2 \tag{7J}$$

$E_{Amplifier}^{CH-CH}$ = energy required for the transmitting data packets between two adjacent cluster head for the amplifier to maintain an acceptable signal-to-noise ratio in order to transfer data messages reliably.

$E_{Amplifier}^{SN-CH}$ = energy required for the transmitting data packets between sink node and cluster head for the amplifier to maintain an acceptable signal-to-noise ratio in order to transfer data messages reliably.

$E_{Electronic-energy}^{CH-CH}$ =Electronic energy degenerated during the transmission between two adjacent cluster heads.

$E_{Electronic-energy}^{SN-CH}$ =Electronic energy degenerated during the transmission between sink node and adjacent cluster head.

E_{tx} = amount of energy used by each node at the time of transmitting data packets.

E_{rx} = energy used for receiving data packets.

Measurement of distance between two cluster heads is done using the following formula

$$d_{xy}\sqrt{(x1-x2)^2 + (y1-y2)^2} \tag{8}$$

Where (x1, y1) and (x2, y2) are coordinates of reference nodes and d_{xy} is the distance measured between two adjacent cluster heads and the notation d_{xy} and d are same.

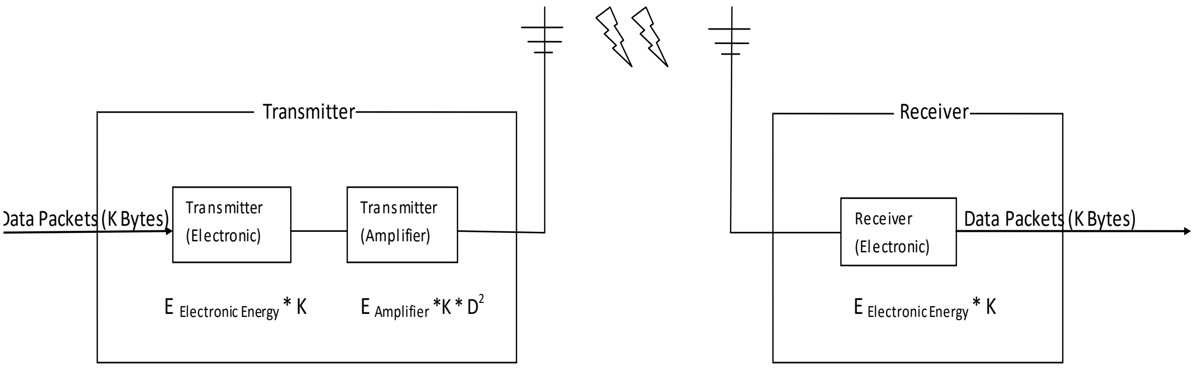

Figure 3. Basic block diagram of WSN communicating devices.

Now in terms of minimizing the total energy transmission and using the proposed ACO algorithm, the optimized path has been established as shown in Figure 5.The data used from

Table 1. Now we have applied the coverage optimization for the targeted area and the corresponding coordinate of active cluster head node (S_i,P_j: see equation 8-9) has been plotted and surprisingly it has been exactly matched with the coordinates of the first phase cluster head position already detected by the ACO algorithm. After getting an efficient path through the meta-heuristic algorithm i.e., ACO we tried for coverage optimization to cover maximum area and we have used DE-QPSO hybrid algorithm as the optimization technique. Here by maximizing the area coverage we can claim that our designed network is an efficient network with respect to minimization of energy consumption. Here comparison has been made between Coverage Ratio vs. Range [meter] as depicted in Figure 6.

Coverage area optimization

Coverage Optimization in Wireless Sensor Networks (WSN) is a necessity for achieving a reliable network because, by this type of optimization, a WSN covering a large area or 3D space can have a reduced number of nodes covering the same space under a sink node. The total WSN power consumption, network cost and efficiency throughput is directly related to its space coverage and the WSN covering more space can secure more reliability. Therefore, if we can maximize the space coverage of the WSN, or more precisely if the covered range can be maximized for each individual node, then a more reliable WSN can be developed. Reliability improvement of WSNs is perceptibly a significant problem because an efficient and reliable network can ensure errorless, robust, and efficient communication. Reliability in WSNs depends upon a multitude of factors such as coverage optimization, cross-layer optimization, communication protocol optimization, packet size optimization, power optimization, duty cycle optimization, and topology control optimization.

In this paper, a new and efficient hybrid algorithm is suggested for resolving the optimization problem of coverage maximization in WSNs. The proposed approach uses two metaheuristic algorithms, namely Differential Evolution (DE) and Quantum Particle Swarm Optimization (QPSO).DE is based on iterative modifications of candidate solutions for a specific objective function in the real number environment, requires the tune-up of a minimal number of parameters in comparison to other meta-heuristic algorithms, and has the self-organizing ability. On the other hand, the QPSO adopts the quantum behaviour of particles used in Particle Swarm Optimization (PSO), where the particles find new improved positions or solutions within a search space with the help of a velocity vector, to obtain the global optimal solution from a comparatively less modified local optimal solution. These two algorithms are hybridized such as we can obtain the optimal solution for WSN coverage.

In this paper, the target network area which has been also considered as the monitoring area is denoted as D in the two-dimensional planes. We assume there are N numbers of WSN nodes in the plane. Here sensor nodes are considered as the particle (individual) in the hybrid algorithm. Supposing wireless sensor network nodes have the communication radius “d” i.e. the range of each sensor node to make communication with adjacent nodes. The definition of coverage ratio (Bin et al. 2011) is as follows. The coverage ratio is the ratio between the covered area by the entire nodes of the total area and the total monitoring area. The coverage area is the sets of the covered area by all active nodes and the value of coverage ratio is in between 0 to 1.In this paper detection probability or probability of availability of a sensor node can be represented by A(i,j) it can be formulated as,

$$A(i,j) = \begin{cases} 1 & d(s_i, p_j) \le d_0 \\ 0 & otherwise \end{cases} \tag{9}$$

Where do is the threshold transmission distance. $d(s_i,p_j)$ is the Euclidean distance of the sensing range. The detection probability of sensor i on the point j is given as (s_i,p_j). Furthermore, it is assumed that all WSN sensor nodes are homogeneous, and their locations are known. In this paper, the coverage ratio is considered as the objective function. The coverage ratio is the ratio between the total number of coverage point and the total number of discrete points. Here coverage point indicates the covering target point of a wireless sensor network.

Now coverage ratio (Bin et al. 2011) i.e. A can be represented as follows,

$$\mathbf{A} = \mathbf{max}\left(\frac{\cup_{\mathbf{i=1}}^{\mathbf{N}} \mathbf{SC_{d(si,pj)}}}{\mathbf{S}}\right) \tag{10}$$

Where, S is the total size of the limited area, N is the number of the WSN nodes. The whole sensor network's coverage should be the coverage sets of all WSN nodes. $C_{d(si,pj)}$ is the coverage requirement for the Euclidean distance of the sensing range.

5. Numerical Result analysis

In this section the energy minimization problem and maximum area coverage was solved using ACO and hybrid DE-QPSO algorithm respectively. The proposed method was tested using the data of Table 1 using the ACO algorithm and obtained the optimized path for the network, which further helped us to form a robust routing protocol for minimizing energy consumption and maximize area coverage. The obtained coordinates from ACO algorithm has been depicted in the graphical representation using graph paper manually to configure the routing protocol. In the second phase, using hybrid DE-QPSO algorithm coverage area optimization has been done to proof the protocol as a robust protocol in the area of WSN network for transmitting data packets between different cluster heads of the network and the sink node. The graphical representation of cluster GRID and the corresponding cluster head has been depicted in Figure 4 and Path Covered in the GRID representation in Expected Coverage in the very first phase of the routing has been depicted in Figure 5. Figure 5 represent the first stage of optimal path but after degenerating energy of the selected cluster head in next phase another node is selected as the new cluster head.

For the sake of our experiment we have considered the nature of all nodes as static Terrestrial WSNs (Srivastava 2010) , where we can do the deployment of the nodes as per as our requirement which may be called organized deployment. In the time of deployment we also carefully calculated the feasible range of transmitting power of nodes and optimized the numbers of nodes to form the cell of the WSN network. In our experiment the structure of cell is hexagonal and the justification this type of shape has been defined previously. In this way we have calculated the boundary cell should have more nodes than that of internal nodes of the network. In the below mentioned figure we have depicted the structure of network which is called Grid representation (see. Figure 4).
The following parameter values are used in the experiment for the simulating the system (Lande and Kawale 2016).

Parameter	value	Parameter	value
Size of target area	850 x 650 m^2	Data packet size (k)	512 bytes
Total number of sensor nodes	49	Max no. of nodes (in the network)	217
Initial energy	1J	$E_{electronic-energy}$	50 nJ/bit
E_{fs}	10pJ • bit−1 •m−2	Maximum Number of Round	1000

Table 1. Parameters for simulation.

In Table 1, the scale of energy is different for the initial energy, $E_{electronic-energy}$ and E_{fs} and those scales are Joule, Nano Joule and Peta-Joule respectively. So for maintaining equivalency all calculations have been done in Peta-Joule in the Table 2 and Table 3.In this section we have plotted the best path of shortest distances (see Figure 5) obtained from the ACO algorithm by solving the equation 7 to 7H on the basis of the data supplied in the Table 1. As the energy consumption is directly proportional with distance between nodes that's why we have calculated maximum coverage area. We obtained the coordinates of sink node and cluster head as depicted in Table 2 and Table 3.The Table 1 shows the communication between sink node and cluster head, whereas the Table 2 shows the communication between adjustment cluster heads. In the below diagram we are going to show the first phase of path selection until we get the minimum consumed energy for the shortest distance between nodes. Here first phase denotes the consumption of full initial energy (here 1 joule) of a node so that we can declare the node as dead note and in second phase we will not consider that node as participating nodes.

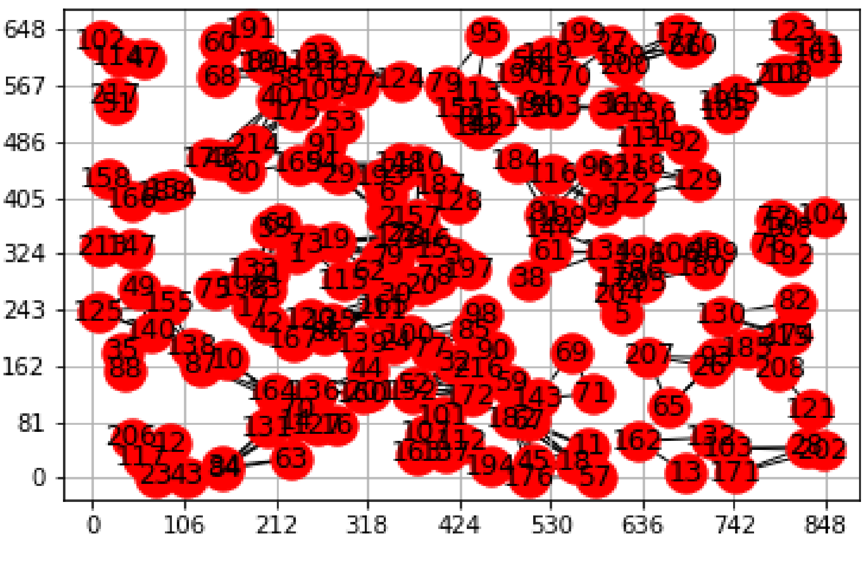

Figure 4. Deployment of WSN nodes for the Expected Coverage Area and

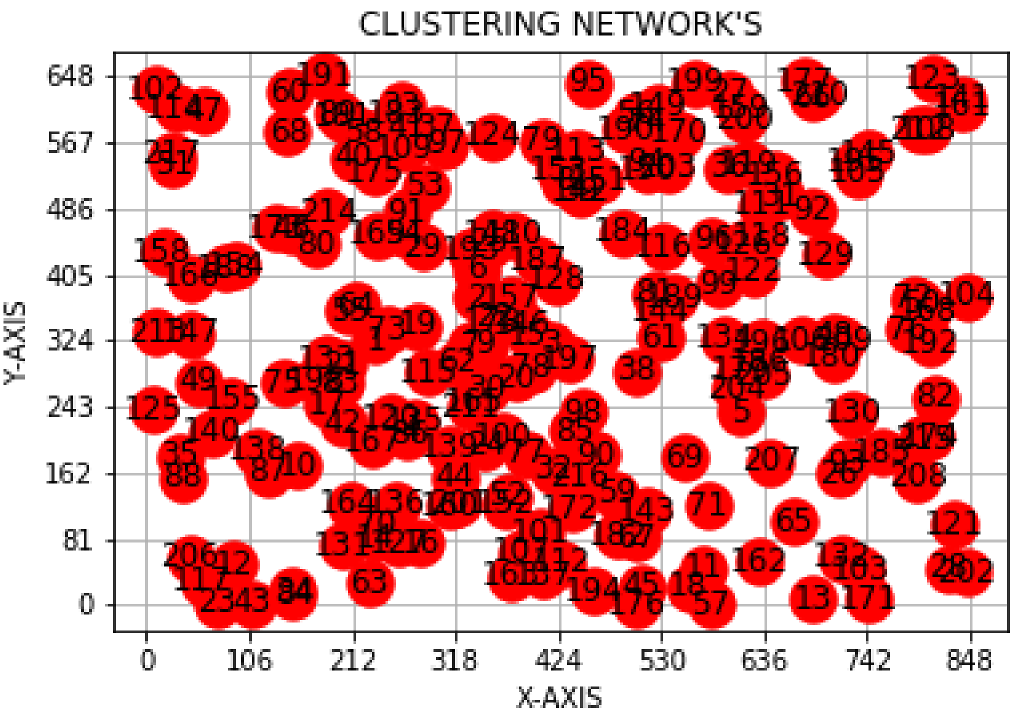

Figure 5. Path Covered in the cluster representation of the network.

6. Numerical Data representation

Among two types of propagation models i.e., two ray propagation model and free space propagation models, the second one is related with distance between communicating nodes therefore in our experiment we have chosen only free space propagation model to show the result.

The representation of a node path has been denoted using Path number, source node coordinator and cell index of destination node. Here cell index is denoted as row and column number of the designated cell. The first cell has been considered as the nearest cell to the sink node and it has been denoted as (r1, c1) means row number one and column number one.

As for example, p1_(0,0)->(r1,c1) denotes the communication of path no one and the source node is the sink node and the destination node belongs cell of the row number one and column number one.

As the path number is associated with a specific communication path therefore we didn't gave each and individual node number in short when the new node of the cell (r_1,c_1) will be selected the path number obviously will be changed.

The numerical result related to the supplied data from Table 1 data has been calculated and represented in the below Table 2 and Table 3.

For Free space Propagation model ($d_{xy} \leq d_0$)

Path number_(sink node)->(row number, Column number)	Calculated threshold distance (d0) in meter	Obtained distance (dxy) between sink node and cluster head in the feasible range (d0 to dxy) after applying ACO algorithm	Sink node co-ordinate (x1,y1) for d0	Cluster node coordinate (x2,y2) for d0	Sink node co-ordinate (x1,y1) for dxy	Cluster node coordinate (x2,y2) for dxy	Minimized E_{tx}^{SN-CH} (in pJ)	Calculated E_{tx}^{SN-CH} (in pJ)	Calculated E_{rx}^{SN-CH} (in pJ)	total Energy consumption before optimization for specific node (in pJ)	total Energy consumption after optimization for specific node (in pJ)	Difference between total Energy consumption before optimization and total Energy consumption after optimization for one node
p1_(0,0)->(r1,c1)	192.093727	188.1586565	0,0	150,120	0,0	147.2,117.2	206311424000.00	206250134732.80		411111424000.00	411050134732.80	61289267.20
p2_(0,0)->(r1,c2)	277.3084925	273.9753639	0,0	250,120	0,0	247.5,117.5	207874560000.00	207949824000.00		412749824000.00	412674560000.00	75264000.00
p3_(0,0)->(r1,c3)	370	367.7152159	0,0	350,120	0,0	348.2,118.2	210338385100.80	210407424000.00		415207424000.00	415138385100.80	69038899.20
p4_(0,0)->(r1,c4)	465.7252409	462.546776	0,0	450,120	0,0	447.4,117.4	213563372339.20	213684224000.00	204800000000.00	418484224000.00	418363372339.20	120851660.80
p5_(0,0)->(r1,c5)	562.9387178	560.0852792	0,0	550,120	0,0	547.6,117.6	217648968499.20	217780224000.00		422580224000.00	422448968499.20	131255500.80
p6_(0,0)->(r1,c6)	660.9841148	658.1910969	0,0	650,120	0,0	647.6,117.6	222544507699.20	222695424000.00		427495424000.00	427344507699.20	150916300.80
p7_(0,0)->(r1,c7)	759.5393341	756.6785976	0,0	750,120	0,0	747.5,117.5	228252160000.00	228429824000.00		433229824000.00	433052160000.00	177664000.00
Energy saving using ACO algorithm after optimizing the consumed energy for the communication between sink node and first cluster head of every path												786279628.8

Table 2. Data for the communication between sink node and first cluster head

Path number_(sink node)->(row number, Column number)	Calculated threshold distance (d0) in meter	Obtained distance (d_{xy}) between sink node and cluster head in the feasible range (d0 to d_{xy}) after applying ACO algorithm	Sink node co-ordinate (x1,y1) for d0	Cluster node coordinate (x2,y2) for d0	Sink node co-ordinate (x1,y1) for dxy	Cluster node coordinate (x2,y2) for dxy	Minimized E_{tx}^{CH-CH} (in pJ)	Calculated E_{tx}^{CH-CH} (in pJ)	Calculated E_{rx}^{CH-CH} (in pJ)	total Energy consumption before optimization for specific node (in pJ)	total Energy consumption after optimization for specific node (in pJ)	Difference between total Energy consumption before optimization and total Energy consumption after optimization for one node
p1_(r1,c1)->(r2,c2)	86.02325267	78.77867732	150,120	200,190	152.6,122.6	197.4,187.4	205054201036.80	205103104000.00	204800000000.00	409903104000.00	409854201036.80	48902963.20
p1_(r2,c2)->(r3,c1)		85.17088704	200,190	150,260	202.4,192.4	147.6,257.6	205097127116.80			409903104000.00	409897127116.80	5976883.20
p1_(r3,c1)->(r4,c2)		79.891927	150,260	200,330	152.2,262.2	197.8,327.8	205061436211.20			409903104000.00	409861436211.20	41667788.80
p1_(r4,c2)->(r5,c1)		85.27602242	200,330	150,400	202,332	148,398	205097861120.00			409903104000.00	409897861120.00	5242880.00
p1_(r5,c1)->(r6,c2)		81.00567881	150,400	200,470	151.8,401.8	198.2,468.2	205068776243.20			409903104000.00	409868776243.20	34327756.80
p1_(r6,c2)->(r7,c1)		85.39601864	200,470	150,540	201.6,471.6	148.4,538.4	205098699980.80			409903104000.00	409898699980.80	4404019.20
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p1												140522291.2
p2_(r1,c3)->(r2,c4)	86.02325267	79.33523807	250,120	300,190	252.2,122.2	297.4,187.4	205057805516.80	205103104000.00	204800000000.00	409903104000.00	409857805516.80	45298483.20
p2_(r2,c4)->(r3,c3)		85.26206659	300,190	250,260	302.3,192.3	247.6,257.6	205097213132.80			409903104000.00	409897213132.80	5890867.20
p2_(r3,c3)->(r4,c4)		80.72719492	250,260	300,330	251.8,261.8	297.8,327.8	205065093120.00			409903104000.00	409865093120.00	38010880.00
p2_(r4,c4)->(r5,c3)		85.24834309	300,330	250,400	302,332	248.2,398.2	205098061004.80			409903104000.00	409898061004.80	5042995.20
p2_(r5,c3)->(r6,c4)		80.44874144	250,400	300,470	251.3,401.3	298.2,468.2	205073417011.20			409903104000.00	409873417011.20	29686988.80
p2_(r6,c4)->(r7,c3)		85.22159351	300,470	250,540	301.8,471.8	248.4,538.4	205098480435.20			409903104000.00	409898480435.20	4623564.80
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p2												128553779.2
p3_(r1,c5)->(r2,c6)	86.02325267	79.33523807	350,120	400,190	352.5,122.5	397.7,187.7	205057805516.80	205103104000.00	204800000000.00	409903104000.00	409857805516.80	45298483.20
p3_(r2,c6)->(r3,c5)		85.26206659	400,190	350,260	402.3,192.3	348.2,258.2	205097763635.20			409903104000.00	409897763635.20	5340364.80
p3_(r3,c5)->(r4,c6)		80.72719492	350,260	400,330	352.2,262.2	398.4,328.4	205066931404.80			409903104000.00	409866931404.80	36172595.20
p3_(r4,c6)->(r5,c5)		85.24834309	400,330	350,400	402.1,332.1	347.9,397.9	205097667788.80			409903104000.00	409897667788.80	5436211.20
p3_(r5,c5)->(r6,c6)		80.44874144	350,400	400,470	351.9,401.9	397.9,467.9	205065093120.00			409903104000.00	409865093120.00	38010880.00
p3_(r6,c6)->(r7,c5)		85.22159351	400,470	350,540	402.6,472.6	348.2,538.2	205097481011.20			409903104000.00	409897481011.20	5622988.80
	Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p3											135881523.2

Path number_(sink node)->(row number, Column number)	Calculated threshold distance (d0) in meter	Obtained distance (d_{xy}) between sink node and cluster head in the feasible range (d0 to d_{xy}) after applying ACO algorithm	Sink node co-ordinate (x1,y1) for d0	Cluster node coordinate (x2,y2) for d0	Sink node co-ordinate (x1,y1) for dxy	Cluster node coordinate (x2,y2) for dxy	Minimized E_{tx}^{CH-CH} (in pJ)	Calculated E_{tx}^{CH-CH} (in pJ)	Calculated E_{rx}^{CH-CH} (in pJ)	total Energy consumption before optimization for specific node (in pJ)	total Energy consumption after optimization for specific node (in pJ)	Difference between total Energy consumption before optimization and total Energy consumption after optimization for one node
p4_(r1,c7)->(r2,c8)	86.02325267	80.03111895	450,120	500,190	452,122	497.7,187.7	205062347980.80	205103104000.00	204800000000.00	409903104000.00	409862347980.80	40756019.20
p4_(r2,c8)->(r3,c7)		85.36462968	500,190	450,260	501.8,191.8	448.4,258.4	205098480435.20			409903104000.00	409898480435.20	4623564.80
p4_(r3,c7)->(r4,c8)		79.7527429	450,260	500,330	452.2,262.2	497.7,327.7	205060526080.00			409903104000.00	409860526080.00	42577920.00
p4_(r4,c8)->(r5,c7)		85.23485203	500,330	450,400	502.5,332.5	448.2,398.2	205097573580.80			409903104000.00	409897573580.80	5530419.20
p4_(r5,c7)->(r6,c8)		80.44874144	450,400	500,470	451.9,401.9	497.9,467.9	205065093120.00			409903104000.00	409865093120.00	38010880.00
p4_(r6,c8)->(r7,c7)		85.24834309	500,470	450,540	502,472	447.8,537.8	205097667788.80			409903104000.00	409897667788.80	5436211.20
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p4												136935014.4
p5_(r1,c9)->(r2,c10)	86.02325267	79.33523807	550,120	600,190	552.5,122.5	597.7,187.7	205057805516.80	205103104000.00	204800000000.00	409903104000.00	409857805516.80	45298483.20
p5_(r2,c10)->(r3,c9)		85.29021046	600,190	550,260	601.8,191.8	547.9,257.9	205097960243.20			409903104000.00	409897960243.20	5143756.80
p5_(r3,c9)->(r4,c10)		79.47439839	550,260	600,330	552.2,262.2	597.5,327.5	205058710732.80			409903104000.00	409858710732.80	44393267.20
p5_(r4,c10)->(r5,c9)		85.27602242	600,330	550,400	602.1,332.1	548.1,398.1	205097861120.00			409903104000.00	409897861120.00	5242880.00
p5_(r5,c9)->(r6,c10)		80.72719492	550,400	600,470	551.6,401.6	597.8,467.8	205066931404.80			409903104000.00	409866931404.80	36172595.20
p5_(r6,c10)->(r7,c9)		85.23485203	600,470	550,540	602.1,472.1	547.8,537.8	205097573580.80			409903104000.00	409897573580.80	5530419.20
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p5												141781401.6
p6_(r1,c11)->(r2,c12)	86.02325267	79.19608576	650,120	700,190	652.1,122.1	697.2,187.2	205056901939.20	205103104000.00	204800000000.00	409903104000.00	409856901939.20	46202060.80
p6_(r2,c12)->(r3,c11)		85.20856764	700,190	650,260	702.2,192.2	647.7,257.7	205097390080.00			409903104000.00	409897390080.00	5713920.00
p6_(r3,c11)->(r4,c12)		80.30952621	650,260	700,330	651.9,261.9	697.8,327.8	205064176435.20			409903104000.00	409864176435.20	38927564.80
p6_(r4,c12)->(r5,c11)		85.23485203	700,330	650,400	701.8,331.8	647.5,397.5	205097573580.80			409903104000.00	409897573580.80	5530419.20
p6_(r5,c11)->(r6,c12)		79.47439839	650,400	700,470	652.4,402.4	697.7,467.7	205058710732.80			409903104000.00	409858710732.80	44393267.20
p6_(r6,c12)->(r7,c11)		85.36462968	700,470	650,540	701.8,471.8	648.4,538.4	205098480435.20			409903104000.00	409898480435.20	4623564.80
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p6												145390796.8

p7_(r1,c13)->(r2,c14)	86.02325267	80.03111895	750,120	800,190	751.9,121.9	797.6,187.6	205062347980.80	205103104000.00	204800000000.00	409903104000.00	409862347980.80	40756019.20
p7_(r2,c14)->(r3,c13)		85.29021046	800,190	750,260	801.8,191.8	747.9,257.9	205097960243.20			409903104000.00	409897960243.20	5143756.80
p7_(r3,c13)->(r4,c14)		79.61356668	750,260	800,330	752.2,262.2	797.6,327.6	205059617587.20			409903104000.00	409859617587.20	43486412.80
p7_(r4,c14)->(r5,c13)		85.19577454	800,330	750,400	802.4,332.4	747.8,397.8	205097300787.20			409903104000.00	409897300787.20	5803212.80
p7_(r5,c13)->(r6,c14)		80.1703187	750,400	800,470	751.7,401.7	797.5,467.5	205063261388.80			409903104000.00	409863261388.80	39842611.20
p7_(r6,c14)->(r7,c13)		85.20856764	800,470	750,540	802.2,472.2	747.7,537.7	205097390080.00			409903104000.00	409897390080.00	5713920.00
Energy saving using ACO algorithm after optimizing the consumed energy for the communication path p7												140745932.8

Table 3. Data for the communication between different cluster head

The proposed ACO algorithm has been run for 50 times to get the best result among those run. The problem (see equation no 5, 6 and 7) has been solved considering a different set of random numbers in the feasible set of constraints (see equation no 5A to 5H, 6A to 6M and 7A to 7J). The proposed algorithm has been solved using the Python programming language in the Anaconda environment of Windows operating system. In this experiment/simulation, a run is considered a successful run if we obtained the solution of the problem, either the same valued result or better than the known best-found solution.

From Table 2 and Table 3 we can calculate total energy saving for the first phase of communication between sink node and different cluster head to cover the whole area and that is 1756090368.00 pj/sec. Therefore we have calculated that 6-7 days of the lifetime of the whole network can be saved with respect to un-optimized Wireless Sensor Network. In the second phase, the path will be changed after consumption of the initial energy store of the corresponding cluster head and so on up to the full energy draining of the selected cluster head.

After minimizing the energy consumption we have also optimized the coverage area as already discussed early. In this case study, different values of Coverage ratio with respect to range has been depicted obtained by different algorithms (Tao et al. 2007).Here a Hybrid algorithm is introduced and compared with the quantum behaved PSO and the Differential evolution (DE) algorithm. In order to verify the hybrid and individual algorithms, iterative optimization techniques performed with some fixed environmental constraints (Tao et al. 2007). Result obtained through simulation by QPSO algorithm, DE algorithm and the hybrid algorithm is depicted in Figure 3.In this case study the range of coverage area has been compared with the coverage ratio, which is a parameter to consider the signal strength.

Here we have shown the comparison between coverage ratio and range of coverage area between DE, QPSO and DE-QPSO and also with the un-optimized method. From the above picture, it is clear that the coverage ratio is much higher in case of DE-QPSO in comparison to DE, QPSO, DE-QPSO and un-optimized method with respect to the same range (0 to 50 meters).

The proposed hybrid algorithm (DE-QPSO) has been run for 50 times to get the best result among those run. The problem (see equation no 10) has been solved considering a different set of random numbers in the feasible set of constraints (see equation no 9). The proposed hybrid algorithm has been solved using the Python programming language in the Anaconda environment of Windows operating system. In this experiment/simulation, a run is considered a successful run if we obtained the solution of the problem, either the same valued result or better than the known best-found solution.

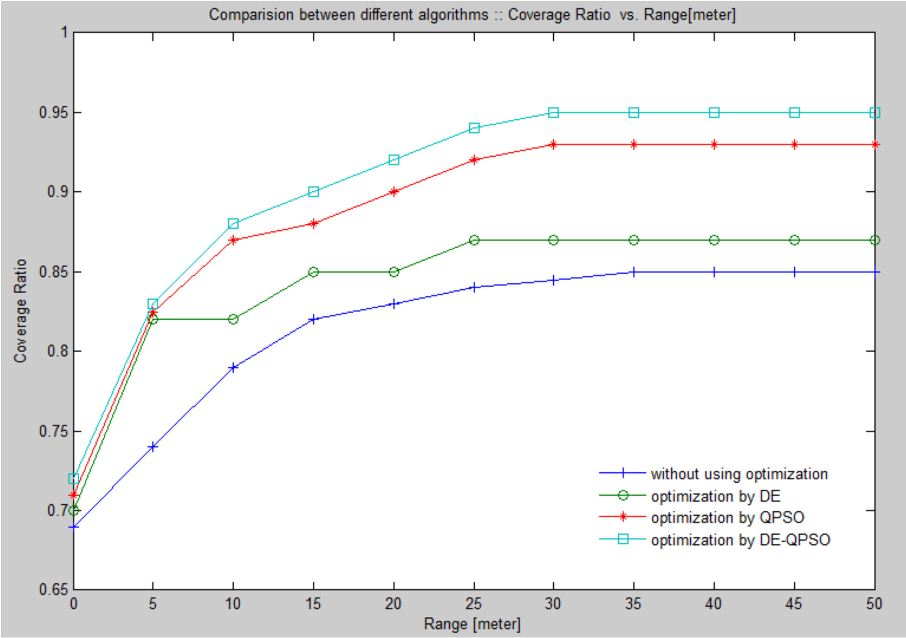

Figure 6. Comparison between different algorithms :: Coverage Ratio vs. Range[meter] for one node

7. Conclusion

The main aim of this paper is to minimize the energy consumption as well as maximize the target coverage area in Wireless Sensor Networks. To minimize the power consumption of a particular Wireless Sensor Network at first, we tried to minimize the traversal path to cover each and every cell of the particular path as well as the traversal path between sink node and cells. The minimizing technique that we have used is Ant Colony Optimizations. Now after getting the optimized path we designed an efficient network keeping mind all the constraints. After that, we have tried to maximize the coverage area optimization using a hybrid algorithm i.e., DE-QPSO algorithm. In this network configuration we have used only random deployment of WSN nodes and we have studied other two types of deployment processes (S - pattern deployment and spiral deployment) which we could use in future and compare with the existing one.

In this paper, coverage ratio has been maximized with respect to a range of coverage of WSN and it has been defined as maximum sensing coverage region problem for randomly distributed WSNs over a specified bounded region. Here a hybrid algorithm using DE and QPSO is proposed to solve this problem. The simulation results show a satisfactory improvement of coverage ratio over a range which implies the improvement of reliability. The sensor’s mobility in the limited region can also realize the coverage optimization and improve the coverage performance of the networks.

For further research, one can improve the proposed hybrid approach using advanced recombination (crossover), mutation operators for DE and different variants of advanced QPSO. We have used QPSO Algorithm because we have focused on the convergence for the local optimal not the global optimal.

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