بسم الله الرحمن الرحيم

In the name of Allah,
the Most Beneficent,
the Most Merciful

1. Optimization (systems)

2. System theory

Maximization of Lifetime in Wireless Sensor Networks Using Ant-Colony Optimization (ACO)

MS Research Thesis

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Dedication

I dedicate this thesis to my beloved Ami and Abu. They sacrificed all their life for me, my brothers and sister to see us successful in all the fields of life.

I could not find words to present them reward of all they have done for me. Any way I thank them for all their honest efforts and prayers. May Almighty ALLAH bless them beautiful and long life.

AMEEN

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Declaration

I hereby declare that this thesis, neither as a whole nor as a part there of has been copied out from any source. It is further declared that No portion of the work presented in this thesis has been submitted in support of any application for any other degree or qualification of this or any other university or institute of learning.

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Abstract

Wireless Sensor Networks (WSN) is use to sense the target area. It is implemented in very harsh environment so the battery plays an important role because it cannot be changed or recharged. It is important to maximize the lifetime of network. Various researchers have addressed this problem at various layers of the protocol stack.

In random deployment, a large number of sensors are deployed without any particular order. As a result more than one sensor may be covering same the area. These sensors become functional at the same time which results in the wastage of battery resources. One strategy is to make disjoint subsets of the sensor nodes such that alternate subsets of nodes operate to cover the whole area at alternate intervals of time. We propose to use Ant-Colony Optimization (ACO) to find the disjoint subsets of nodes. We consider two cases. Firstly, we used disjoint subsets for point coverage secondly for target areas converge. We compare proposed scheme with GAMDSC [28], STHGA [29] and MCMCC [40] results proves that the proposed approach is better than these previously proposed schemes.

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Chapter 1 Introduction

1.1 Wireless Sensor Networks

Wireless Sensor Network (WSN) is a new technology to monitor physical area. It is advance and currently used technology. Wireless Sensor Network consists of few or larg number of nodes that sense the specific area or used for specific monitoring. These sensors have ability to sense the environment or observe the environment for what they were designed. These are autonomous nodes which observe the physical area or the different environmental situation like temperature, sound, pressure etc. and transmit their sensing information through the network to main location. The improvement in wireless sensor networks was initiated by military application like battlefield, many industries application like temperature measurement, fire alarming and different consumer applications and so on [1]. Wireless Sensor Networks usually consists of number of nodes or sensors and these node/sensors are arranged in different topologies. Every sensor process the data so have a microprocessor, for wireless data communication there are radio chips and sensor sense the required information. The sensors are very low cost, low power consumption, much functional and a small device. These small sensors are able to sense the information, process it and then communication with each this communication is normally over Radio Frequency channels or simply RF channel.

1.2 Sensor

The design of Micro Electro Mechanicals system (MEMS) and different wireless communication technology have advanced the sensors [2]. Therefore, every sensor has capability of computation, communication and storage. Normally Sensor node consists of the following main parts.

- Power source or battery
- Memory
- Micro Controller
- Transceiver
- ADC
- Sensor

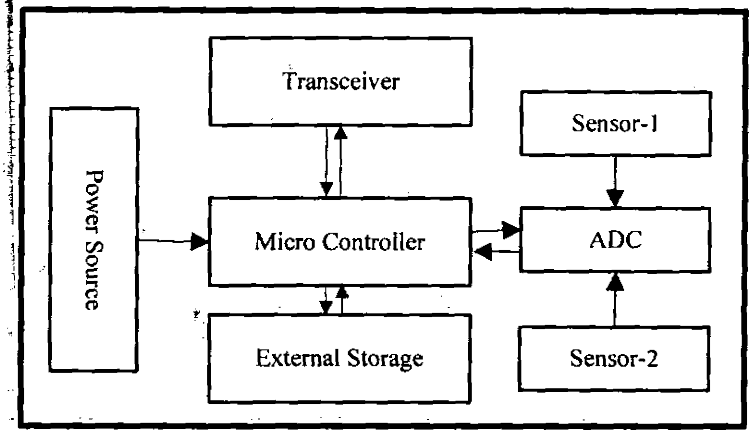

Fig. 1.1: Sensor Parts

Controller

In the sensor, the first part is controller that processes the information. Generally, the controller is microcontroller and other controllers are desktop microprocessor, FPGA, ASICs etc. These are used in many embedded systems because of low in cost, easy to program and consume very low power use.

Transceiver

Sensor node normally uses ISM band, which is free radio spectrum. Wireless communication use three types of communication ways such as Radio Frequency, Infrared and Optical and Laser communication. Optical communication use low power but it required line of sight and it is more dependent on suitable environmental conditions. Infrared have limited communication capacity. The communication based on Radio frequency is very suitable for the WSN application, license free communication. It has different frequencies 173, 433, 868 and 915 MHz and 2.4 GHz. The spreader and recipient are two different function, these two function are combined into single device are called transceivers.

Memory or Storage

Memory is another very important part. It is a kind of memory that on-chip storage of microcontroller memory and off-chip RAM or known Flash memory. RAM memory is used because it's low cost and can gain some storage. Memory is very important in WSN application. There are two types of memories that are normally used in sensors devices storing memory use for saving personal information and other type of memory is program memory that is used for programming the sensor or devices.

ADC

Analog to Digital Converter used for converting the analog information into digital information. ADC device convert continuous information into discrete information. It provides an isolated measurement in sensors.

Power source or battery

For sensing the information sensor need battery. Sensors consume battery for communication and processing information. In sensors, energy is stored at two points, one is battery and other is capacitors. The batteries used in sensors are rechargeable and non-rechargeable too. They use electrode called Nickel cadmium, secondly nickel metal hydride and third is lithium ion. Another source of recharge is solar energy. Two power saving polices are used in sensors Dynamic Power Management and Dynamic Voltage Scaling.

Sensors

Sensor is hardware devices that sense the condition like pressure, sound and temperature etc. Sensors are divided into three main categories first, is passive second is Omni-directional and third is active sensors. Every sensor has his own sensing range. These sensors sense the information from the environment and send that information to main processor through the buses.

1.3 WSN Topologies

When we deploy sensors to establish wireless sensor networks we can use different topologies [3]. Every type of application requires reduction of cost, complexity and reliability. So in sensor networks we need this type of topologies that reduce cost, reduce complexity and enhance reliability. Generally, there are five types of topologies that are discussed below:

- Star
- Ring
- Bus
- Tree
- Mesh

Star Topology

A hub is centralized device used for star networks. Every node cannot directly communicate to each other; they need centralized hub for communication. So in star topology hub is considered as a server and other nodes as clients.

Ring Topology

Ring topology every node perform equal function, no need of centralized node. A message travels in the ring in one direction, if ring is crack down all communication will be misplaced.

Bus Topology

Messages are broadcasted on bus to all networks. Every node checks the destination address and send message to destination. This type of topology simply listen messages and cannot response for retransmission of any message.

Tree Topology

This topology is the combination of both peer-to-peer and star topology. In this topology networks use central node that is known as communication roots. On level low root node is known central node. This lower level is like star topology.

Mesh Topology

In mesh topology communication is between nearest neighbors. Every node is connected to every node in entire network. This topology is very reliable but very complex.

1.4 Wireless Sensor Network

In wireless sensor network, sensors are used to sense. These sensor devices are very small and good for communication. Sensors have many issues but one important is battery lifetime. Therefore, energy is issue in wireless sensors. It is used to monitor the area, temperature, measuring pressure and so on. Sensors are deployed in an area, that time sensors have a base station other are sensors nodes and some time node have cluster. These are shown in below diagram.

Sensor nodes: Nodes sense information from environment and send to the cluster.

Cluster Nodes: Many nodes combine and send information to their main node called cluster node. Cluster received the information and send back to base station.

Base station: Base station can manage the whole sensors in network.

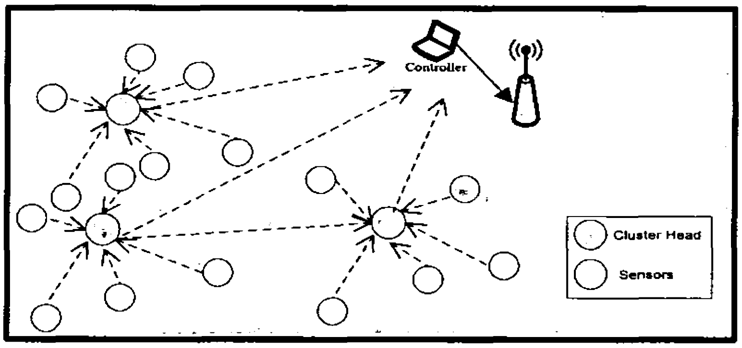

Fig. 1.2: Wireless Sensor Network

1.5 Application of WSN

Following are the application of wireless sensor network application.

1.5.1 Area Monitoring

An important application of WSN is area-monitoring application. In this wireless network, sensors are deployed in a region where some area is to be monitored. Examples are: military use sensor for enemy intrusion, in private sector sensors are used for monitoring of oil or gas pipelines etc.

1.5.2 Environmental Sensing

Environmental sensing used for the earth science research, this type of application can be uses for the other purposes as sensing volcanoes, forests and so on. Other environmental sensing applications are Air pollution monitoring, Forest fires detection, Landslide detection etc.

1.5.3 Industrial Monitoring

There are many applications of WSN in Industrial monitoring. Some are Machine health monitoring, Water/wastewater monitoring, Agriculture, Structural monitoring and so on.

1.6 WSN Issues

The sensor nodes is WSN have issues like limited in power, computational capacity and memory. Because of limited power capacity sensor nodes cannot transmit up to long distances.

WSN are implemented in very crucial environment where recharging or changing of the sensor's battery is generally impossible. Therefore, maximization of lifetime for a sensor becomes more important. There are many methods proposed for efficient use of energy [4]. Two of them are sensing coverage and other is network connectivity are basic issues when all nodes are active in complete area coverage at least double of its sensing range. It mean more nodes or sensors are covered a single field area.

1.7 Deployment of Sensors

There are two way for deploying sensors to cover target area: Control deploying and random deployment [5]. Control deployment is easy because it based on plan but random deployment is not a easy task, finding the position of sensor is difficult because of very large area. Some time in random deployment, sensors are deployed from airplane or another way.

1.8 Scheduling in Sensors

In random deployment situation, scheduling is an important for controlling sensors activities to increase the lifetime of network [6]. Sensors have two operation modes active and sleep mode, in active mode sensors consumes energy but in sleep mode very low almost nothing. Different methods are used for changing sensors modes. In distributed and localized sensors periodically check their neighborhood and then decides to change their modes.

1.9 Cover Sets in Sensors

In complete cover area, large numbers of sensors are deployed. In order to increase the battery life we only selects the subset of sensors those who cover whole area and others subset remained in sleep mode When battery life of selected subset ends then other subset switches to active mode.

1.10 WSN Coverage Architecture

Following diagram show the whole coverage area to an $L \times W$, where L is consider length of complete coverage and W is width. There are many sensors deployed in random methods. Sensor sensing rage is r and r_i is the sensing range of i^{th} sensor. Below in the Fig. 1.3 many sensors have covered the same field at the same time it is noted that one field is covered by two or more sensors. In this situation if we use only one sensor at a time and other remain in sleep mood then the lifetime of the sensors can be extend.

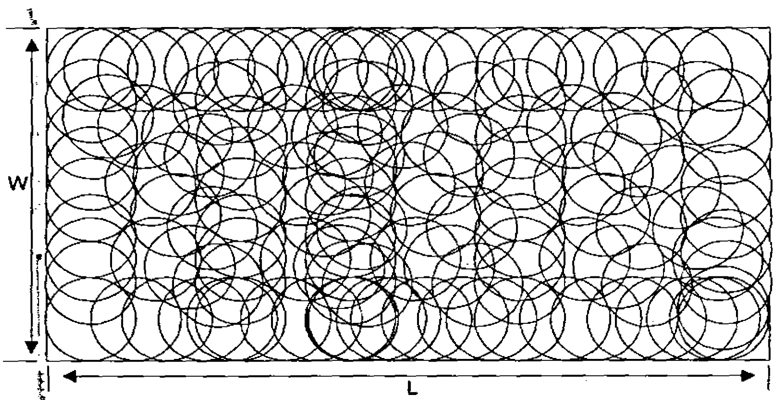

Fig. 1.3: Complete Coverage Area [40]

1.11 Our Objective

Our objective is to finding the subsets that covered whole area. Two different subsets contain only different sensors mean one subset have different sensors than other subset is called disjoint set. So main objective is to find the highest number of disjoint sensor cover sets in WSN this process is also known as disjoint set cover problem or set k-cover problem [7].

In our proposed approach, we use ACO (Ant Colony Optimization) to change the incomplete cover set to a complete cover set. In this process the remaining sets still maintains the complete coverage area. In this scheme, ACO will perform number of Point coverage and area coverage. We proposed this technique as an alternate of previous methods. In the base paper Genetic Optimization technique is used, many other techniques [8]-[11] to solve this types of problem; we use ACO because it showed better results than Genetic Algorithm and others previous methods.

1.12 Thesis Organization

In chapter 2, we discussed literature survey related to our problem then we discuss problem statement in chapter 3 after that in Chapter 4 we discussed proposed solution and chapter 5 presents Implementation and produced results. Chapter 6 is related to conclusion and future work.

Chapter 2 Literature Survey

2.1 Literature Survey

In previous chapter, we have seen the major challenges in wireless sensors networks one major of them was to extend the duration of the whole network. The main objective of our work is to efficiently utilize sensor's energy so it extend the lifetime of the whole sensors network. In this chapter, our focus is to discuss the recent energy conservation methods for wireless sensors networks and detailed history of energy conservation techniques. After discussing the background of energy conservation methods, we also discussed the evolutionary computing method and their usage in wireless sensors networks. At last, we will narrow down in evolutionary computing techniques use for energy conservation in wireless sensors networks and make the lifetime as long as possible.

2.2 Energy Conservation Techniques in WSN's

[10] Othma et al. discuss the energy consumption and find where more energy consumes. They discussed that energy consumption in communication is higher as compared to the computation. It has been discuss that communication of one bit may use more energy as compared to the computation of few thousands instructions. In communication sensor uses energy this energy set levels if sensors drop that level use and other radio energy. Therefore, we need mode of nodes. One mode known as active mode and other is sleep. Change of modes depends on the networks activity. This method is known as duty cycling. This process is calculated as period in which node is active during the complete time of the sensors life times.

[11] Eshghi et al. discussed the clustering techniques and made comparison to different energy conservation techniques. It has been shown that the techniques of clustering in wireless sensors networks prolong the network lifetime. To achieve the objective they used

clustering algorithm. Some algorithm make networks uniform distributed and each cluster in networks is load balanced. Load balancing methods are important to get enhanced performance and for improving the lifetime of overall networks. In clustering algorithm, there are two level of load balancing. First, the utilization of energy among the nodes and the nodes CH must be stable. Then the all nodes carry load of CH equally. The second level of load balancing dissipation of energy among CHs must be stable as well. Therefore, the CHs that are loaded with additional duties have to be conveying fewer member nodes, which denote that these CHs should have a lesser communication range.

2.3 Sensor's Scheduling For Energy Conservation

In wireless sensors networks we can save lifetime of sensor in different ways. Saving the life time of sensor can give us guarantee to maximize the life time of whole networks. On the best and more important method of saving, the life of sensors is scheduling. Scheduling is a technique that changes the sensor's mode from sleep to active and vice versa.

In our problem we used scheduling technique and make disjoint set. After finding of disjoint sets one can decide that which disjoint set should work at a time when its lifetime end then other disjoint set that covered the whole area can switches to active mode from sleep mode.

[12] YE, ZHONG, et al. discuss the ROS techniques for scheduling. This technique is known as Route Oriented Sleep (ROS). ROS scheme allow sensors to changing their mode depending on routing information and complete network activity. Sensors in networks change their operational mode according to networks activity without losing their communication information and networks coverage. The techniques discussed in this paper used routing order and decide effective sleep scheme in network. In network some sensors may have very long route path, other may have short and specified path for routing. In this case long path

sensors to sleep mode, and these sensors are active when these are used for short and specified path. This technique is used for load balancing in network and for the finding of best and short path for routing information as well. Then the information that moves on shortest path are in active mode and long path nodes are in sleep mode. That's why nodes consumes very low energy for this scheduling method.

[13] YE, F. et al. proposed PEAS technique. PEAS is a scheduling technique and known as distributed probing based density control method for tough sensing coverage. It makes different group of sensors that covers the entire network area and one set made in active mode assures that first set can completely covers the whole area. Other sets of nodes are in sleep form to save power. Frequently, the set of sleeping nodes wakes up and check other set of nodes working mode within probing range. If the other nodes are not working in its probing range then next set needs to changes their modes from sleep to active. This technique does not fully cover the original sensing range after rotating off some sensors so; it does not assure entire coverage.

2.4 Non-disjoint Algorithms

Z. Abrams et al. [14], first described the Sensor Energy efficient Scheduling for k-coverage (SESK) problem and further resolve this problem by using Distributed Energy-efficient Scheduling for k-coverage DESK. This algorithm determines and schedules the non-disjoint subsets of nodes that can assure the k-coverage over the effective area where consumer can change k.

Algorithm works as: first brings up to date current residual energy e_i, and gather information, then makes the N_i-element list L of its one-hop neighbors. After that, it sends a message to its neighbors. If it receives active message then it updates coverage level else it received the sleep then the current number of dependent neighbors is decreases by one. Otherwise if it receives the *gosleep* message then Remove sj out of list L. At last a message is broadcasted to all sleep and active sensors list Z. Abrams et al. in [14] used three estimate algorithms for variation of the K-cover set Problem but these three algorithms can't assure the complete coverage of whole area.

Liner Programming technique [15] is proposed by Berman et al. Auther proposed a technique to compute all cover sets in whole area and then deduce the best possible duration for each cover set .Their methods was based on the approximation of the Gar and Konemann algorithms [20], whose estimate factor is $(1+\varepsilon)(1+2\ln^{n})$ for any $\varepsilon > 0$. Author also point out the problem of searching the least weighted nodes set that partially cover the network monitoring area. This problem is known as set q-Cover problem for solving this problem used greedy algorithm are used. After searching minimum weight of nodes next step is to account communication cost. Steiner Tree was used to achieve an approximate solution. All algorithms implemented in programming language C++ and use Workstation Ultra-60.

M. Cardei et al. [16] discussed the non-disjoint covers set problem. Linear Programming (LP) is used to solve the target area coverage problem for non-disjoint cover sets. LP algorithm have highest complexity that was O (m^3n^3) where *m* is number of covers and *n* is the number of sensors. Authors also suggested that a greedy algorithm which have low complexity was $O(dk^2n)$ where *d* is the number of nodes that covers the area that is associated with a smallest amount of sensors and *k* is the number of targets. Sensors scheduling mechanism can be accomplished using three methods. First, sensors send their position related information to the base node which is known as Base Station or BS. Secondly, the BS performs the scheduling algorithm and then transmits the schedule regarding sleep and active. The last method works as: every sensor schedules itself for sleep or active mode. For efficient communication of data from sensor nodes to the BS LEACH algorithm and PEGASIS are used. These algorithms can also be used at the same time.

Dhawan [17] also worked on maximizing the life time of sensors networks. Author focused on maximizing duration of target-covering nodes in the network in which each sensors can adjust its sensing range. The problem considered in this paper is known as Sensor Network Lifetime Problem (SNLP). Sensors have covered more fields in order to save energy, selects only those subsets of nodes that cover every part of target area. A mathematical form of the problem using a linear program with exponential number of variables and explain this linear program using the approximation algorithm of Garg-Könemann[20]. Linear program formulation works as following.

$$Maximize : \sum_{j=1}^{m} tj$$

where, b_i is the battery for sensor i, and, $C_{ij} = 0$ if sensor i is not in sensor cover j, C_{ij} = g(d), if sensor i is in sensor cover j with a sensing range fixed to d and g is a function of energy over distance. In this paper author used Garge Konemann algorithm with its approximation ratio (1+e). This algorithm is used also for f-approximation that was used to find column minimizing length.

2.5 Disjoint Algorithms

S. Slijepcevic and M. Potkonjak [18] suggest a disjoint centralized algorithm for the area coverage problem. In this paper they focused on the idea of fields in target area. One sensor can cover more than one field or more sensors can cover more fields. However, one field is covered at least one sensor. The best regular position of sensors that these nodes covered area with minimum number of sensors or nodes. For this purpose use mathematical equation that is

$$P_{area} / N \times r^2 \pi = 2\pi 3 / \sqrt{27}$$

Where p_{area} is the size of the observe area, N is the minimal number of nodes to cover the whole area, and r is the sensing range of nodes. It is considerd that the range of the nodes is extensively smaller than the dimensions of the covered or whole area. Proposed scheme primarily covers the more meagerly populated fields, which are called critical fields. After the collection of a node that covers a critical field, the algorithm excludes all other nodes covering the same field. The complexity of the proposed algorithm which computes the disjoint sets is ($O(n^2)$).

Authors propose [19] an algorithm to solve same above problem using another method graphs. They build an undirected graph G= (V,E) , where V is the set of nodes and E the set of edges such that the edge $(u,v) \in E$ and E if and only if u and v are within each other's sensing range. The objective was to find the highest number of "dominating sets". To get this authors use a graph colorings procedure. The dominating sets do not assurance the coverage of the entire area. The complexity of the heuristic which computes the disjoint sets from the colored graph is $O(n^3)$.

J. Wu and M. Cardei [21] the coverage problems for sensor networks can be categorized into three wide types. These are

a) Area coverage: - The major aim is to observe an area.

b) target coverage :- Where the main goal is to cover a set of targets

c) Breach coverage: - The aim here is to reduce the number of uncovered targets.

Cardei and Du [22] propose an algorithm used to the random target coverage problem solve. These types of problem is formulated as an area coverage problems and verify that is NP-Complete problem. Authers identify the disjoint-set coverage problem originally introduced by Slijepcevic and Potkonjak [30]. They suggest a heuristic to work out the disjoint sets. In order to compute the highest number of covers, authors convert the problem into a maximum-flow problem. At resultants this type of problem solved by using Mixed Integer Programming, which heuristically construct the final number of cover sets. Authors [22] illustrate a minor enhancement in the number of formed sets as in [19] but there is a extensive delay in execution time. Time complexity of algorithm depends on the complexity of the Mixed Integer Programming scheme [22].

D. Zorbas et al. [23] present an efficient algorithm. This algorithm coverage the disjoint cover set. Algorithm search best sensors that cover the area and use regular node selection approach, this approach attempt to find minimum possible nodes that area cover. This algorithm is based B{GOP} algorithm but it improve cost function called Critical Control Factor (CCF). CCF is capable both disjoint and non-disjoint. Once Critical Target has been created a node that covers the goal should be selected. If further sensor exists, then the sensor most appropriate for selection will be the one with the maximum contribution. Two distinction of the algorithm are described: The Static-CCF algorithm and Dynamic-CCF.

2.6 Optimization Algorithms

Normally optimization techniques are linear, nonlinear, and quadratic programming; Newton based method, and interior point scheme etc. The computational complexities increase exponentially with size of problem. More and more sources required and cost of mathematical models engines used for linear, nonlinear, and quadratic programming make them unattractive for resource constrained nodes. That why researcher new area is the experimental algorithms such as Differential Evolution (DE), Genetic Algorithm (GA), Fuzzy logic(FL), Bacterial Foraging Algorithm (BFA), Particle Swarm Optimization (PSO) and Ant colony optimization. GA makes possible improvement of the population creation by generation using three methods such as crossover, mutation and selection [24]. Differential

Evolution (DE) is like as to GA, although it used differential operator [25], which produce a new solution vector by mutating an existing one by a difference of arbitrarily chosen vectors. BFA models the foraging actions of bacteria that used combination of straight line and arbitrary movements to reach nutrient-rich position [26].

[27] Ant colony optimization is too metaheuristic algorithms used for combinatorial optimization problem. ACO first algorithm proposed in 1991 and now it is in form of different variation. This algorithm use genetic and bionomic algorithm, main idea of this algorithm inspired by the behavior of actual ants.

Below some literature survey of genetic algorithm that used in cover set problem and finding disjoint cover set in wireless sensors networks.

The technique use Slijepevic and Potkonajak [19] and Cardie and Du [22] have more computational time, to reduce this computation by using Genetic Algorithm (GA). Lai et al.[28] introduce GA for solving point coverage problem called it Genetic Algorithm for Maximum Disjoint Set Covers (GAMDSC). This algorithm base on the GA, in this process they use genes and chromosomes, each gene in the chromosome as an integer index of the set that the sensors together. Using genetic operation their algorithm able to get optimal solutions, Genetic used mutation, crossovers and combination for finding optimal solution. Limitation of that paper is, only suitable when the numbers of target and nodes are small. Other is only use for point coverage. The main important drawback of this paper is that genetic algorithm required more numbers of inputs for producing small number of output. For this reasons it use more computation cost.

Hu et al. [29] proposed the GA enhance their aim to solve disjoint set covers problems for maximizing the duration of WSN. Their proposed algorithm called Schedule Transition Hybrid Genetic Algorithm (STHGA). This algorithm can be applied on both area and point coverage. An important feature of their algorithm is that it used a forward encoding method for the illustration of chromosomes in the population. Other are uses some effective genetic and nodes schedule transition operations. The performance of the proposed STHGA has been compared with the MCMCC [40] and GAMDSC [28]. Result shown that the proposed algorithm can achieve high-quality solutions with a much faster optimization speed. But same problem here genetic used it's required more inputs for producing optimal solutions.

Now we find out drawback in genetic algorithm, that time another parallel search area is Particle Swarm Optimization (PSO). In different paper we find out Particle Swarm Optimization (PSO) is better than Genetic algorithm (GA) so it's used may be better. Below some literature survey related to Particle Swarm Optimization that approved it is better than Genetic Algorithm

Particle Swarm Optimization (PSO) [30] is an optimization computing method that is based on bird flocking. In [30], author proposed a set of potential solutions are called particles that are initialized arbitrarily. During every generation, each particle estimate its fitness continually until the fitness assure the given threshold. The solution in each generation is updated using the following equations:

$$v_{id}(t) = w \times v_{id}(t-1) + c_1\vartheta_1(p_{id} - x_{id}(t-1)) + c_2\vartheta_2(p_{gd} - x_{id}(t-1))$$
$$x_{id}(t) = x_{id}(t-1) + v_{id}(t)$$

Where v is the particle velocity; x is the particle Position;

t is the quantity of iterations (generations); c_1,

and c_2 are two positive constants

Particle's best position is denoted as p_{id}

While p_{gd} is the global best.

Genetic Algorithm (GA) [31] is also another optimization method based on biological evolution. In this optimizations method use string called chromosomes. Chromosomes represent in the forms of binary or real number. To check the goodness a fitness function is use. Using these chromosomes produce new generation, normally use three methods that are selection, crossover and mutation. These methods continue until convergence is reached or gain highest generation.

2.7 GA for Energy Conservation in WSN's

Already discussed genetic algorithm above in different techniques, it is biological evaluation process. The methods are used in biological system can be used for wireless sensors networks. Genetic algorithm (GA) is computational method that depends on genetic operations like recombination, selection, crossover and mutation. Genetic algorithm (GA) is used in wireless sensors networks to find optimal solutions in wireless sensors networks.
For improving performance in the weighted clustering algorithm (WCA), Turgut et al. [32] used the Genetic Algorithm. In mapping procedure, information about cluster head and its members has been stored in chromosomes. This technique balances the load of the network and minimizes the number of cluster heads. Through recurring genetic operations, the fitness of the algorithm is get. Proposed techniques have better result than old techniques.

[33] Chien-Chih et al. proposed new method order-based GA. This new order –based results shown that the order-based GA can get much more covers than Most Constrained Minimally Constraining Heuristic (MCMCH) in much less time than Maximum Covers using Mixed Integer Programming (MCMIP) the MCMCH and MCMIP both are two different techniques that are used to solved cover set problems. That is, the proposed scheme provides a solution to the tradeoff among solution quality and efficiency in solving the Set K-Cover problem. These results confirm that the proposed order-based GA is efficient and capable for wireless network performance and whole area networks life time.

2.8 PSO for Energy Conservation in WSN's

[34] There a number of issues in Wireless Sensors Networks such as deployment, energy issues, networks lifetime etc. These issues formulated as optimization problem.

The recent optimization techniques are requiring more computational efforts and consumption of time and other high cost problem. Recent optimization problem grow exponentially as the increasing the problem size, that types of solutions are required more memory and high computational resources. Bio inspired techniques for optimization problem are efficient methods. After GA and other bio inspired optimization techniques is Particle swarm optimization (PSO) , ease of understanding, high and efficient solution and most important the speed of convergence are strengths as compared to the genetic algorithm.

[35] Discussed the routing problem to find out path from source to destination by using Particle swarm optimization (PSO). The wireless sensors networks use hierarchical. Every group has a sensor that performs as the cluster head. Sensors that belong to a cluster send out their information packets to the cluster head, which forwards it to the base station. A node that performs as a cluster head for a extended duration exhausts its batteries prematurely. This calls for an optimal cluster-head selection mechanism. Further, cluster assignment process can affect the network performance and longevity. Clustering is too NP-hard optimization problem, which PSO can handle welled and efficient. Cluster-head selection is not a single time action; therefore, the simpler the optimization algorithm, the improved the network effectiveness is.

2.9 ACO in WSN

[36] M. Dorigo et al. briefly provided the survey of ACO with respect to other evolutionary Computing specially in GA. It also provides theoretical results from the survey on Ant colony optimization. Convergence results review, relation between different Ant Colony

Optimization algorithms and other method for optimization were discussed periodically. After describing the draw back from GA it concludes that ACO is comparatively better than GA.

Rahul Putha *et al.* in [37] claimed that for large-scale trails ant colony optimization produced better and consistent results over genetic algorithm. The authors also claimed that ACO reduced execution time and this characteristic make is useful in real scenarios.

N. Binti Sariff *et al.* in [38] compared the performance of ACO and GA in Robot paths planning in global static environment. Comparison in made in terms of speed and total number of iteration taken to reach on an optimal path that is most suitable. Results showed that ACO is faster in speed and takes less number of iteration as well. Another character of ACO makes is better than GA is that its parameters are easily adjustable.

Chapter 3 Problem Statement

3.1 Problem Definition

Among others techniques for energy preservation and efficient utilization, one possible solution is the scheduling [12], [13], [14], [32]. In random deployment of sensors nodes, where the area of coverage of the sensors overlaps [18], one can employ scheduling there. For scheduling to work optimally one need to find maximum number of disjoint sets or group of sensors nodes, which in ideal case, completely cover the target area [23]. Our problem is to find maximum number of disjoint sets of sensors that completely cover the target area and then verify efficient utilization of energy so that the lifetime of the networks is prolonged.

We need to make use of sensors energy in efficiently way. There are number of different techniques available for the efficient usage of sensor energy. One step that can be taken for this goal is to schedule the sensor regarding ON (active) and OFF (sleep). In order to make sure complete area coverage, a huge number of sensors are deployed densely to the area in random deployment manner. Scheduling is a main method for controlling sensors' behavior to prolong a network's lifetime [12]-[13] in this way only a limited and optimized number of sensors are in active mode at a time that provide complete coverage to the whole target area and remaining sensors retained in sleep mode.

In controlled deployment, we have prior information regarding the deployment environment but the scenario is different with random deployment where we do not have any sufficient information about the deployment region/area, this type of deployment can be achieved from the airplane or by any other mean. In such kind of deployment, there many unexpected problems situation can occur. In this way more than one sensor can cover the same region (which means that sensors are overlapped) which will be the wastage of energy if all the sensors are in active mode at the same time. Although scheduling is very effectively used to increase the life time of the network but in the base paper approaches it is tackled using genetic algorithm. There is much criticism on the genetic algorithm such as: it increases the search space exponantionaly, it may end on a locally optimum solution, slow in terms of speed, doubtable accuracy [36]-[38]. We tried to tackle this issue by intelligent scheduling procedure while using the ant colony optimization (ACO) as literature survey tells us that it is better in accuracy and speed as well [36]-[38].

3.2 Problem Scenario

As the sensors are battery powered and has limited active mode time. We need to improve the life time of sensor network in a way that selects only a specific set of sensors (k-sensors, where k is a pre-defined number) that are active at the present time and are providing complete coverage to the network area so that life time of our sensor network could be increased. The remaining (N-k sensors, where N is the total number of sensors deployed in the whole target area) should be scheduled to be in the sleeping mode which would be active later on. Now some of our methodology is becoming clear is that our goal will be to find the maximum number of disjoint sets which will include the sensors that will be able to cover the complete target area with minimum number of sensor nodes[18]-[23] at once. When most of the sensors which were presently active from a disjoint set will die down (more technically it means that, those particular sensors will be disconnected from the rest of the network). Then a new set that was found earlier should replace the dead/expired set of sensor nodes to get the complete coverage to maintain the connectivity in the target area. As there will be only one disjoint set in active mode at a time and this set will completely cover the target area, which will able us to achieve our rultimate goal that was the increase in the life time of a sensor network. In literature, this problem is called disjoint set k-cover problem and proved that it is NP-complete problem [7]-[8]. Suppose a set $S = \{S_1, S_2, \ldots, S_N\}$ of sensors are deployed in an $L \times W$ target area, the objective of the sensor set covers problem is to find the maximum number T of disjoint complete cover sets of sensors and the corresponding cover sets S_i, satisfying:

1) Each set $S_i = \{si_1, s_{i2} \dots s_{i|Si|}\}$ subset of S of sensors should cover the whole target coverage, where $|S_i|$ is the number of sensors that are activated in the i^{th} schedule, i =1, 2... T

2) Each sensor will be in only one cover set, which is S_i intersection $S_j = \varphi$ Where $i \neq j$, and i, j =1, 2... T.

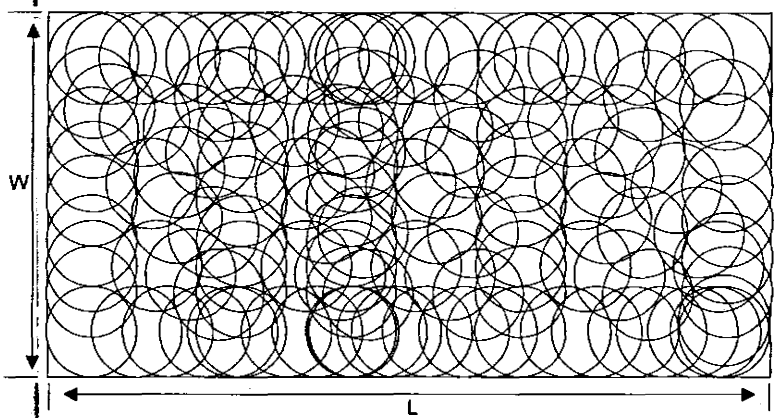

Fig. 3.1: L × W Whole Area Coverage

The scenario tells us the subsets covered by the whole area. These subsets contain different sensors and once a sensor is used in any sub set it should not be used in any other set again. The set produced in this way will be known as a disjoint set. As the number of disjoint set will increase the there will be bright chances to increase the lifetime of the network to its maximum.

Chapter 4 Solution and Methodology

4.1 Solution and Methodology

In this chapter we discussed the use of ACO. In our proposed solution we implemented ACO (Ant Colony Optimization) to change the incomplete disjoint sets to complete disjoint sets. Our proposed methodology made sure that the remaining set covers target area completely. Proposed scheme is applied on target point (Point coverage) and area coverage (Whole area) problem. The proposed ACO approach is an alternate to the previously proposed approaches GAMDSC [28], STHGA [29] and MCMCC [40]. Previously Genetic Algorithm Optimization technique [31] and different other techniques have been used to solve these type of problems [8]-[11]. We proposed ACO because in literature [37]-[38] we found that it shown better results than Genetic Algorithm [36]. The previously proposed approaches GAMDSC [28] and STHGA [29] also used GA [31] so we proposed ACO instead of GA. First, we discussed the concerned processes in the solution scenarios and after that we will integrate these processes for final optimum solution.

4.2 Ant Colony Optimization (ACO)

Ant colony optimization (ACO) is a population-based meta-heuristic that can be used to find approximate solutions of difficult optimization problems. Heuristic means to find and meta-heuristic means to find at a higher level.

4.2.1 Heuristic

There are many problems exists which cannot be solved in real time and exact solutions so exact solutions cannot be found for those problems. Approaches that can be used to solve this kind of problems are known as heuristic based algorithms. These approaches have ability to find an optimum solution to these problems; a solution that is hopefully nearer to exact solution while keeping the short time in view as well. These approaches use experience based knowledge to find optimal solution [27].

4.2.2 Meta-heuristic

Meta-heuristics are the algorithmic concepts that enable us to find heuristics to solve combination optimization problems. These approaches works by enhancing initially produced solutions to get optimal solution that is nearer to exact solution [27]. Ant Colony Optimization is a meta-heuristic approach that is used to solve the combination optimization problems. Ant colony, genetic algorithms, particle swarm optimization and Bee Colony etc. are kind of evolutionary approaches used to solve optimization problems. We discussed in literature survey that the problem of finding the disjoint sets to monitor some environment belongs to the combination optimization problem that has been solved using different evolutionary methods. We propose Ant Colony optimization as opposite to genetic algorithm to solve this problem because to the best of our knowledge we could not find that ant colony optimization have used to solve this problem. Literature survey tells us that ant colony optimization has better performance as compared to genetic algorithm in terms of iterations taken to converge to some optimum solution [37]- [38]. Ant colony optimization is easy to adjust parameters [36], [27].

ACO is inspired by the foraging behavior of ants. It searches the domain more effectively and reduces the computation time [27]. The distinct feature of our scheme is that it applies both point area coverage and whole area coverage and makes disjoint sets using same geographical area. The implementation of the proposed method discussed below in a systematic procedure, including the initialization and different operations of ACO.

4.3 Working of Proposed Approach

Mathematical Problem Formulation

Consider an area of dimensions as L×W as shown in Fig. 4.1 the whole area is divided into girds. The size of grid is adjustable depending upon the problem and required quality of solution. The smaller size of grid is preferable to achieve better results [29], [39]. We assumed that N number of sensors have been deployed in the target area. A unique assigned number is assigned to every sensor and to very grid as well. The numbers assigned to grids are very much helpful to check that what percent of whole area is covered, which sensor covered which grid and what grids are common. After the division of area into grids, we checked whether the whole area is covered or not as it is our basic requirement to cover the complete are.

Fields formed by the deployment of sensor. Because we need the field view of the target area, so we find fields in the whole deployment area. After forming fields, we analyze critical fields and critical sensors. Critical fields and sensor are both special and important, as without including these fields and sensor we cannot cover the complete area. The critical sensors actually defined as the Ŧ.

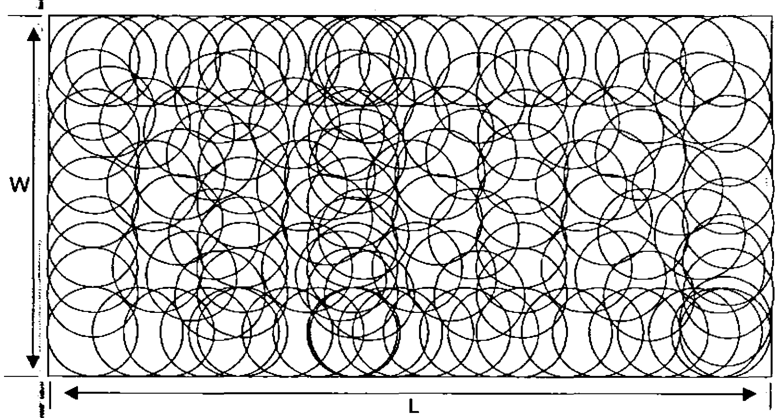

Fig. 4.1: L×W Area

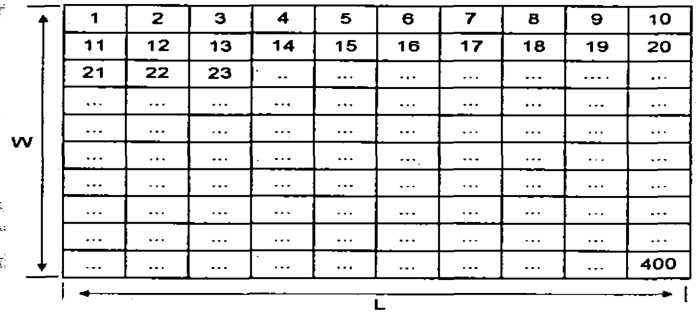

Fig. 4.2: L×W Area with Grids

Fig 4.1 Based on our previous discussion, consider N=100 sensors in the deployment area which have assigned unique ids s_1, s_2, s_3, s_4 ....s_{100}. The coverage area is also divided into 400 grids, as shown in Fig 4.2.

Initialization

Initially all the sensors are turned ON at the time of deployment it is assumed that the deployed sensors are covering the whole area completely, which is 100m*100m.

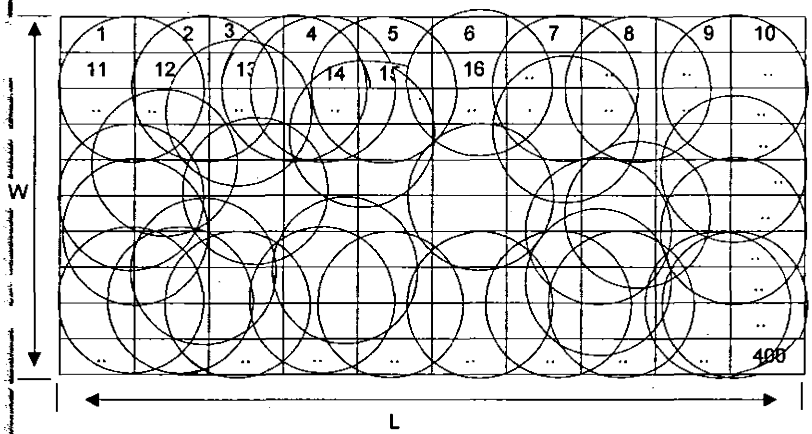

Fig. 4.3: L×W Area with Sensors

To calculating grid size we use R radii of the circular coverage area of a sensor and R=8 which is the number of grids covered by the each sensor. As shown in Fig. 4.3 each sensor covered different numbers of grids. Ids and grids number of a senor is used to calculate the sensors grids. We assumed that first sensor s_1 has covered the grids {g1, g2, g3, g7, g12, g15, g18, g11} similarly

s_2= {g2, g4........ g6, g7}

s_3= {g4, g17.... g18, g11}

s_4= {g12, g15... g18, g11}

s_5= {g10, g12...g15, g17}

....

....

s_{100}= {g12, g15, g19, g20, g25, g37, g41, g45}

We have to make sure that the whole area is covered by the sensors which are switched ON at a time. To achieve this task, take union of all grids of all the sensors in target area. If the produced union is equal to the total number of grids in area that is calculated at the initial step it means that our initial condition is satisfied. This will lead us to calculate disjoint cover sets in whole or point coverage area.

Fields View of Coverage Area

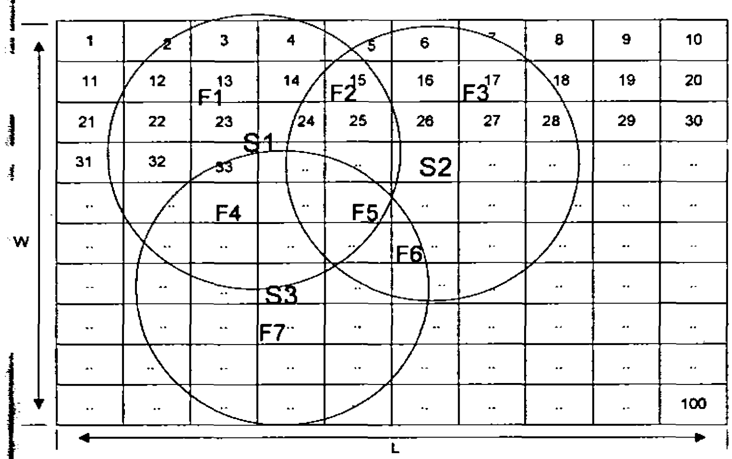

Fig. 4.4: L×W Area with Fields View

For this purpose, we used the concept of fields, as shown in Fig. 4.5, F1, F2 ... F7 are the fields where as S1,S2,S3 are the sensors. The sensing ranges of these sensors are overlapped with the sensing ranges of other sensors. These sensors are covering the same as well as different number of grids. To know the fields covered in common by the sensors, we take intersection of the all sensors one after another. We take sensor S1 with all its covered grids and take its intersection with other remaining N-1 sensors grids. It is assumed that S1 covers the grids {g1, g2, g3, g7} and S_2 covers {g2, g4, g6, g7} we have

$$S_1 \cap S_2 = \{g1, g2, g3, g7\} \cap \{g2, g3, g4, g6, g7\}$$

$$= \{g2, g7, g3\}$$

$$S_1 \cap S_2 \cap S_3 = \{g1,g2,g3,g7\} \cap \{g2,g3,g4,g6,g7\} \cap \{g2,g3,g7,g12\}$$

$$= \{g2, g7, g3\}$$

By the above mentioned steps we found fields F1, F2, F3, F4, F5, F6 and F7 which do no contained common grids. For example field F1 has 4 grids covered similarly field F2 contain two grids etc. Now we take *min* of these values which is 2 this is Ŧ's value. According to Ŧ value it is assumed that the numbers of complete disjoint covered sets in whole area that can completely cover the whole target are at once is two.

Coverage Percentage

The next step is to calculate the coverage percentage of every sensor. We can calculate the coverage percentage with the help of total number of grids and the number of grids covered by one sensor.

$$P_{Si} = (\text{Grids covered by sensor } S_i/\text{Total numbers of grids}) * 100 \quad \text{.............Equ 4.1}$$

P is Coverage percentage of sensors S_i where i=1, 2, 3......100

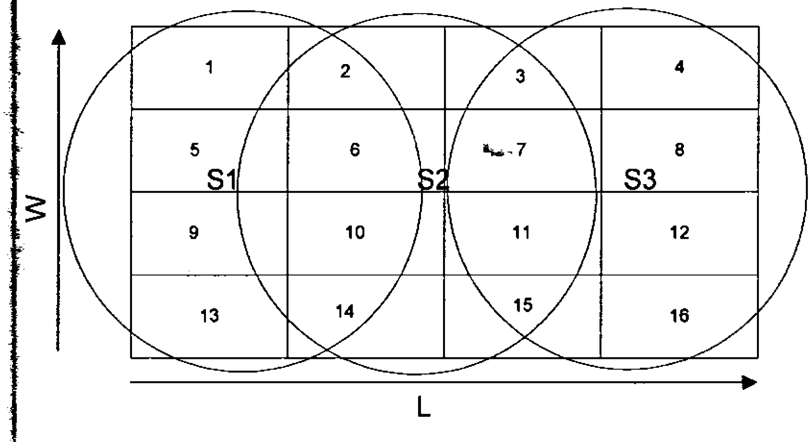

Fig. 4.5: Coverage Area

Fig 4.6 shows 10m×10m area, where three sensors are deployed S1, S2 and S3 and the whole area divided into 16 grids. S1 covered grids g1, g2, g5, g6, g9, g10, g13 and g14 where as S2 covered g2, g3,g6,g7,g10,g11,g14 and g15 and the sensor S3 covered the g3,g4,g7,g8,g11,g12,g15 and g16 grids. Now we calculate the coverage percentage of each sensor, by using above mention formula.

Coverage Percentage of S_1 = (8/16)*100=50%

Coverage Percentage of S_2 = (8/16)*100=50%

Coverage Percentage of S_3 = (8/16)*100=50%

The above calculated coverage percentage of each sensor s_1, s_2 and s_3 is 50% of whole area. Now we can calculate complete coverage percentage of set1.

Set1 = $\{S_1, S_2, S_3\}$

$S_1 \cup S_2 \cup S_3$ = {g1, g2, g3... g16}

Coverage Percentage of Set1 = (Union of all sensor's grids/Total Grids)*100

= (16/16)*100

= 100%

The coverage percentage of set1 is 100%, which means that whole area is completely covered by the sensors in set1.

4.4 Ant Colony Optimization Algorithm

Ant colony optimization is used to search for optimal solution from a search space of feasible solutions. The artificial ants construct the solution by moving on the weighted edges of fully connected graph. While the ants move to the next state they leave a substance on the previously moved edge, which is known as pheromone. When all the ants complete their tour, the amount of pheromone is updated on the edges that are traversed by the ants. The stopping condition can based on some criteria regarding the accuracy, some fix number of iterations or any execution time limit. The resultant solution is the optimal solution [27]. Before assigning an optimization problem to ACO we must mention some parametric values on which this algorithm proceeds.

- Ant: a software agent that move on the edges and produce solutions
- Pheromone: a substance left by the ants which guides the after coming ants to follow that typical path/edge
- Memory: M_K or $Tabu_K$, Ants have some memory that enables them to remember the edges, visited during a tour. This memory can be used to find the shortest tour length.
- Next move: Ants moves to any next feasible (not visited yet in a single tour) state on the base of a probabilistic rule

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum\limits_{k\in allowed_k}[\tau_{ik}(t)]^{\alpha}[\eta_{ik}]^{\beta}} & \text{if } j\in \text{allowed}_k \\ 0 & \text{otherwise}\end{cases} \quad \text{.................... 4.2}$$

α , β are user defined parameters which control the relative influence of pheromone and heuristic information $0 \le \alpha, 1 \le \beta$. In the probabilistic rule τ_{ij} is the amount of pheromone on the edge *i,j*. η_{ij} represent the heuristic information which is the inverse of the distance between node *i,j*. $p_{ij}^{k}(t)$ represents the probability of movement for an ant *k* at time *t* to next state *j* while it is on the state *i*.

- Pheromone update

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij}^{best}(t) \quad \text{..................4.3}$$

$$\Delta\tau_{i,j}^{k} = \begin{cases} \frac{Q}{L_k} & if\,(i,j) \in \text{tour} \\ 0 & \text{otherwise} \end{cases} \quad \text{...........................4.4}$$

ρ Parameter represent the evaporation as in real ants the pheromone evaporates, $0 \le \rho \le 1$. This parameter helps us to have diversity that is the basic theme of the evolutionary algorithms. Q Is a constant that denotes the total amount of information that an ant leaves after visiting all feasible states. L denotes the length of tour that an ant k travelled [27].We used the above mentioned parameters in our proposed method to find maximal number of disjoint sets which will enable us to maximize the life time of wireless sensors networks by using the intelligent scheduling. We set ACO parameters α , β , τ_{ij} , η_{ij} , $p_{ij}^{k}(t)$, ρ , Q, L and assign values to these parameters. In the above scenario equation 4.3 the area is of 100mx100m with 100 sensors, area divided into 400 grids as in [29]. We find Ŧ using above mentioned method which a number of disjoint set that consists of sensors. The numbers of ants, iteration are same as estimated Ŧ because we need minimum number of disjoint set which is equal of Ŧ. Every ant produces different solution at the end of each tour we select a solution that results in highest coverage percentage while using the minimal number of sensors. Ants randomly select start node and calculate the probability to move to the next feasible (a node that can be visited according to the *tabu list*) nodes. For probability calculation the above given formula is used equation 4.2. This probabilistic rule tells the ant to either move to from the current state i to the next j available state or not. There will be no further move if all the feasible states have moved in the current tour. τ_{ij} Initially the pheromone value on all nodes/states is m/C^{nn} [27]. Heuristic desirability η_{ij} is the inverse of distance; we calculate the distance among the number of grids of neighboring overlapping sensors. By neighboring we mean directly connected. For example, we assume three sensors s1, s2, s3 where each sensor is consisting of five grids. The distance between s1 and s2 is computed as total (5) grids covered by s1 subtracted by the overlapping (3) grids between s1 and s2. This gave us the resultant value of 2 that is distance regarding the grids of s1 and s2. Similarly the distance from s1 and s3 can be calculated. For example, s3 is overlapping with 2 grids over s1 then the distance between these is of 3 grids. For η_{ij} we calculate the inverse of the above calculated distances. The greater the distance the η_{ij} values will be less as it is the inverse and vice versa. The parameters α and β are user dependent values that control the relative effect of pheromone trail τ_{ij} and η_{ij} distance desirability. N_i^k Set of feasible states that an ant k can pass through yet in a tour. The memory can be used for several purposes such as: to calculate the shorter distanced tour. At the tour completion this memory is cleared to be used for the next iterations.

Transition probability is used to maintain the balance between pheromone intensity and heuristic information. The values of α, β are bounded as $0 \le \alpha, 1 \le \beta$ [27].

α, β parameters influence in different ways such as: If α= 0 then all after coming ant will follow the same explored path depending upon short distance base. If β=0 the selection will be dependent on pheromone value. If $\alpha > 1$ search will be biased (paths already explored by software agents will be selected which will lack diversity which could lead us to local optimal solution) .To get exposure to the search space we have to avoid the above situations.

Next state selection is dependent of higher probability value. When iteration completes solutions is produced are updated with equation 4.3 and equation 4.4. Pheromone updating is a very important task that wills able ants to converge. Evaporation is used to get diversity and to avoid premature convergence so that bad move of previous solution can be avoided. The pheromone is updated and evaporation is done using equation 4.3. An ant k is the ant that has completed it tour and found one solution and now will update the pheromone using equation 4.3.

After first iteration we obtained seven solutions as we were having seven ants. At the end of iteration the pheromone value is updated using the above equ.4.3 and equ.4.4. As the paths were updated and the pheromone value is changed now in second iteration ants will chose the path that will be having higher level of pheromone. At the completion of first iteration the pheromone value was updated. This procedure will continue until all mentioned iterations are completed. When all iterations that were given by the user at the initialization stage will be completed all the ants will have consensus on one optimal solution. This optimal solution will be a disjoint set that will cover maximum or complete target area with minimum number of sensors.

The sensors that have been selected in disjoint set1 will be subtracted from all the sensors. Now we will find another disjoint set using the same procedure discussed for the first optimal solution, set after first disjoint set may not cover the whole target area if the network deployment is not of dense type. Possible number of disjoint sets will be produced by ants until all the sensor are utilized. Purpose of all disjoint sets to be switched ON is that only some specific number of sensors of a disjoint set is in active mode at a time so that network could remain alive for the long time. It is initial requirements to achieve Ŧ disjoint sets that cover whole area coverage. The disjoint sets that will not be covering the whole area will be assigned some of the critical sensors so they can cover complete area. So in this process we achieve 7 disjoint sets from 100mx100m and the sensing range of each sensor is 20m, with

100 sensors. The number of disjoint sets will be equal to the estimated Ŧ. Our first fitness function is: $Fi = \{Si(\min .si \,\&\, \max .Ci)\}$ 4.6

Where s_i Minimal number of sensors and C_i Maximal coverage percentage of Set S_i.

4.4 Flow Chart Of The Proposed Scheme

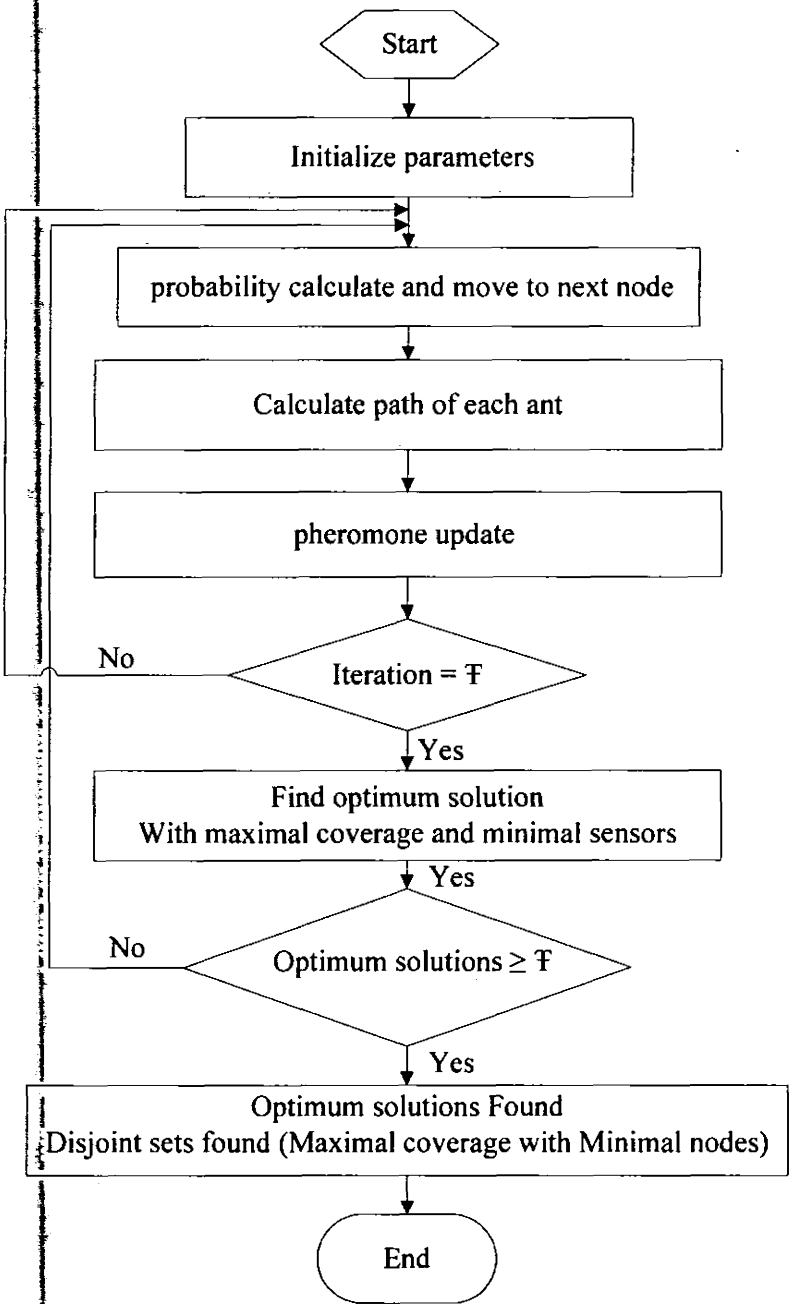

Fig. 4.6: Flowchart of Proposed Scheme

The produced solution set contained different number of nodes, coverage percentage but these sets may have improper placement of nodes due to this improperness less percentage of the whole area can be covered. To cope this problem we need a schedule transition operation. There are three types of schedule transition operations. We adjusted another fitness function that would schedule transition operation [29]. Below we explained that fitness function and then discussed the schedule transition operations.

Fitness Evaluation

Below is the fitness function that is used for scheduling transition operation. This function produces maximal coverage percentage of covered disjoint sets. Fitness function is:

$$f_i = c_i + p_{ci}+1 \qquad \text{4.7}$$

Where ($c_i \geq 1$) which is the number of disjoint complete cover sets $S_1, S_2, \ldots, S_{ci}$ formed after the initialization process is completed. $p_{ci}+1$ ($p_{ci}+1 \in (0, 1)$) representing the coverage percentage of the $(c_i + 1)^{th}$ cover disjoint sets, which are incomplete cover sets where $i = 1, 2, \ldots, m$. If the coverage percentage of the incomplete cover set $p_{ci}+1$ is 1(it means cent percent coverage) then 1 will be added to c_i else the coverage percentage value will be added to $p_{ci}+1$.

4.5 Schedule Transition Operations (STO)

There are three kinds of schedule transition operation which includes (i) Mixed schedule transition (ii) Forward schedule transition (iii) Critical schedule transition. The schedule transition operation utilizes the redundant information between the scheduled sensors for each particle. On the base of the redundant information these schedule transition operations are performed on initially produced disjoint cover sets [29].

4.5.1 Mixed Schedule Transition

As the name tells this transition operation mixes the scheduled transition operation which was redundant sensors between a cover set to the other. At first a sensor is selected on the random base. If the selected sensor is redundant to the corresponding cover set then we change the sensor schedule with a randomly picked complete coverage schedule. If the scheduling number of the sensor remained same (which there is no effect on complete coverage set) then this sensor is moved from complete to incomplete cover set which will be different from the sensor's original schedule. The above process is repeated for k2 which is a user defined parameter which is based on the number of disjoint sets.

4.5.2 Forward Schedule Transition

The forward schedule transition operation is used to enhance the coverage percentage of the incomplete cover set in a better way. After rescheduling sensors among different cover sets by the mixed schedule transition, the forward schedule transition operation schedules the sensors that were repeating from complete cover sets to incomplete cover set. For this scheduling k1 sensors will be selected. If the corresponding sets are redundant then selected sensors will be rescheduled into the incomplete cover set to increase the coverage percentage of incomplete cover sets.

4.5.3 Critical Schedule Transition

At least one critical senor is necessary for a set to cover the whole area and this technique offers it, So it the most effective schedule transition. Once critical field of the critical sensors are covered, there is more emphasize on scheduling sensors to the incomplete sensor set to form complete coverage. In a complete cover set that contains one cover critical field we randomly choose that sensor and it is then checked that set is redundant or not.

4.6 Flow Chart of Proposed Scheme with STO

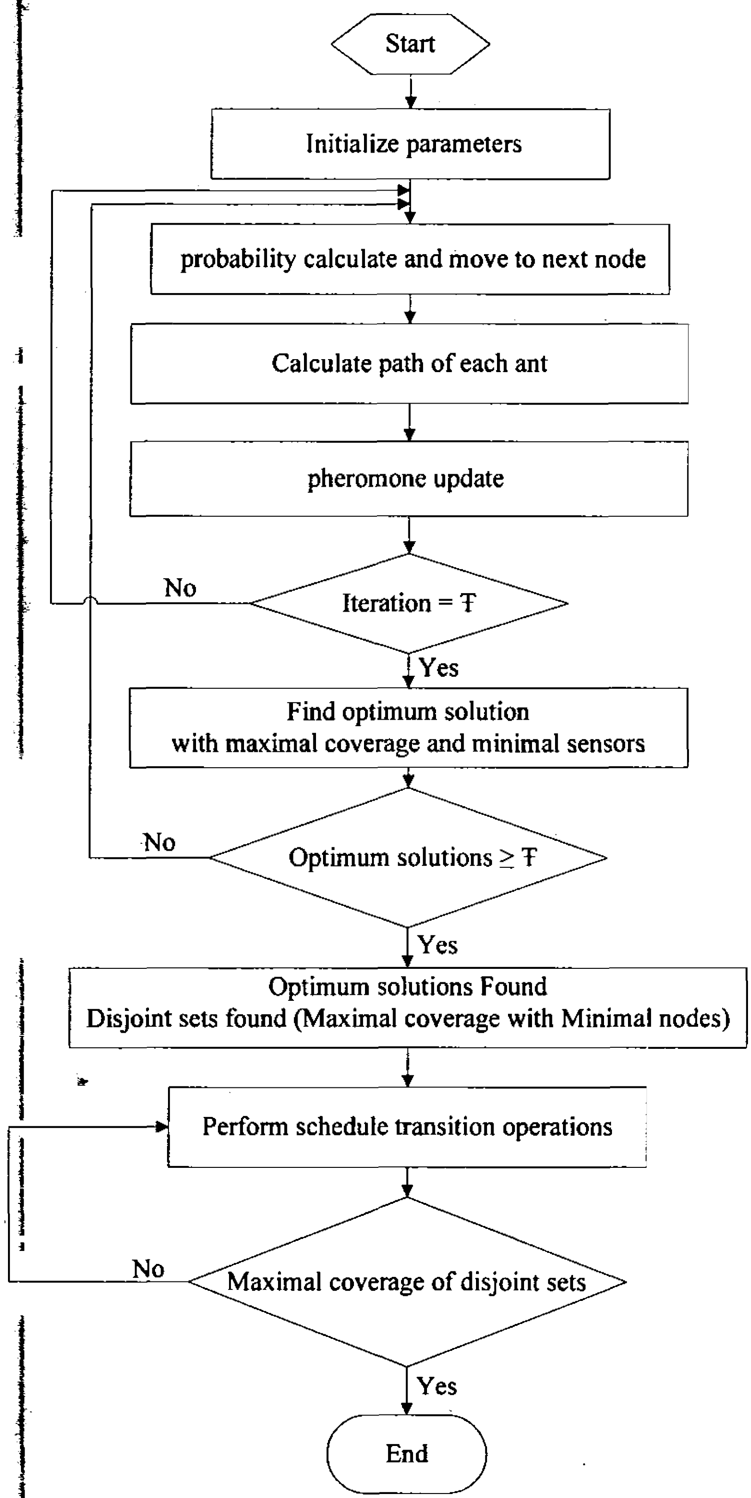

Fig. 4.7: Flowchart of Proposed Scheme with STO

A detailed simulation algorithm is shown in Fig.4.7. All the steps in this flow chart are same as the previous one, one thing which is additional is schedule transition operation. The benefit of this additional step is that it increases the percentage of already disjoint cover sets. At the end we got the desired number of disjoint sets of sensors covering the complete target area. The termination condition of algorithm is the desired number of disjoint subsets of sensors.

Chapter 5 Implementation and Results

5.1 Data Sets

The parameters values are data sets. On the bases of parameters we produce results and compare these results. At first we took $L \times W$ is area where L is a length and W is a width of area, For the purpose of comparison and production of different results area length and width may increase/decrease but in our simulation it is set to 100mx100m as were in the base paper. Then we used N=100 which is the numbers of sensors, R is radii set to eight grids size, which is L/floor [L/(R/8)].

After that we used ACO data sets. Before assigning an optimization problem to ACO we must mention some parametric values on which this algorithm will proceed. We sets $\alpha = 1, \beta = 5$, pheromone evaporation value is ρ=0.5 these parametric values are recommended by Dorigo *et al.* [27]. We varied values of these parameters.

5.2 Implementation Tool

The problem of finding disjoint sets has been solved with different optimizations methods and is being simulated using MATLAB and many other simulation tools. We compare our result to the GAMDSC [28], STHGA [29] and MCMCC [40] they have also simulated in MATLAB. So we too simulated proposed scheme in the MATLAB 7.8.0 (R2008a) with a different technique that was Ant Colony using different number of sensors and radii. The performance could clearly be observed that proposed approach is better in term of time and found more number of disjoint sets.

5.3 System Requirements

We have used Windows operating systems. The system specifications were as follows:

1. Hardware...............Pentium IV 2.8 GHz CPU [28]-[29]
2. Operating system......Window XP
3. Network simulator..... MATLAB 7.8.0 (R2008a)

5.4 Simulation Experiment Results

We compared proposed technique with three others previously proposed algorithms. The final results of implemented proposed algorithm is better than base approaches GAMDSC [28], STHGA [29] and MCMCC[40], which is applied to same problem like our problem finding disjoint sets in cover set problem. It can clearly be seen in Table 5.1, 5.2 and 5.3 that the performance of proposed algorithm is much better than the previous algorithms.

For the ease of comparison, the results have been shown in both tabular and graphical forms with detailed explanation and comparison analysis is also provided below in step by step procedure. First, we compare proposed technique of finding maximum disjoint cover sets using Ant Colony Optimization with the Maximum Disjoint Set Covers (GAMDSC) [28] in Table 5.1. In the Table 5.2 comparison is given with the schedule Transition Hybrid Genetic Algorithm (STHGA) [29] and at last we compared results with Most Constrained Minimally Constraining Covering (MCMCC) [40].

5.5 Result in Tabular Forms

Below in the Table 5.1 first comparison is presented of proposed techniques with the previous method Maximum Disjoint Set Covers (GAMDSC) [28]. From serial 1 to 9 we used different numbers of sensors (N) and varied sensing range R. The best results of both algorithms for each case are bold in table.

5.6 Comparison of GAMDSC

The results of our proposed scheme have compared with Genetic Algorithm for Maximum Disjoint Set Covers (GAMDSC) [28] that is our base scheme in table 5.1. Our proposed scheme results are much better than the previous proposed scheme GAMDSC in all cases. In previous proposed scheme authors used different parameters named No. of fields formed, Ŧ found, average simulation time in microsecond (ms) and OK percentage through which we compared the performance of proposed algorithm to previous. We have compared all these four parameters one by one and observed that the performance of proposed algorithm is better. Below we also discussed the comparisons in detail.

Table 5.1: Proposed Scheme and GAMDSC Results

	Cases		ACO					GAMDSC				
S. No.	N (No. of sensors deployed)	R (sensing ranges)	Nf (No. of fields formed)	T-tilda calculated (Ŧ)	T-tilda-found (Ŧ)	T (Ave. Simulation Time (ms))	ok % (Successful percentage)	Nf (No of fields formed)	T-tilda calculated (Ŧ)	T-tilda-found (Ŧ)	T (Ave. Simulation Time (ms))	ok % (Successful percentage)
1.	100	20	**378**	10	**10**	27.272	100	**382**	7	**7**	126	100
2.	300	15	**674**	14	**14**	312.44	100	**673**	14	**13**	9713	0
3.	300	20	**395**	25	**25**	318.95	100	**400**	29	**25**	10080	0
4.	400	10	**1563**	8	**8**	625.720	100	**1556**	8	**6**	13764	0
5.	400	15	**675**	22	**22**	592.813	100	**676**	20	**15**	13268	0
6.	500	8	**2389**	8	**8**	1325.82	100	**2400**	6	**4**	17413	0
7.	500	10	**1588**	10	**10**	1133.45	100	**1586**	8	**5**	18527	0
8.	1000	5	**6043**	5	**5**	3710	100	**6076**	3	**0**	38105	0
9.	1000	8	**2493**	18	**18**	3220	100	**2498**	5	**3**	37830	0
Some of Additional simulations												
10.	120	20	387	16	16	33.15	100	-	-	-	-	-
11.	150	20	395	12	12	90.50	100	-	-	-	-	-
12.	175	20	392	18	18	139.75	100	-	-	-	-	-
13.	200	20	399	21	21	234	100	-	-	-	-	-
14.	250	20	400	22	22	295	100	-	-	-	-	-

Fields Formed Comparison

The sensors deployed in $L \times W$ covered different number of grids. The grid areas are use to make fields. Field is area or grids that are covered by the sensors. The fields formed by sensors are very important and are used for prior calculation of number of disjoint covered sets in whole coverage area. The number of fields formed in proposed scheme are greater in number and in some cases these are almost equal as shown in above Table 5.1.

Ŧ Comparison

Disjoint set that are prior calculated are known as Ŧ in proposed scheme liked previous scheme GAMDSC [28]. The main goal of proposed scheme is to maximize the number of disjoint sets to maximize the life time of whole WSN. The Ŧ is an important parameter in proposed and already existing schemes, because in proposed scheme it is use to compare results until we gain resultant Ŧ.

In proposed scheme when we compare these Ŧ values to the previous GAMDSC algorithm, it can be clearly seen that the values of Ŧ of our proposed algorithm are always higher as compared to GAMDSC which are present in the above table 5.1 fifth and eleventh column form serial number 1 to 9. There is much difference in result cases like case number 5 to 9. This difference shows much better performance of proposed algorithm as compared to GAMDSC which means that the proposed algorithm is much suitable for finding k-set cover problem as compared to GAMDSC.

Average Simulation Time Comparison

The average simulation time is the time required to find disjoint sets. This time is the total time of execution of whole algorithm. In propose scheme scenario we calculated average time in microsecond (ms). The comparison of average simulation time of proposed and previously proposed schemes has been shown above in table 5.1. From table column 7 to 12 average simulation time is presented.

Above in the table 5.1 we compared the average simulation time of proposed and previous algorithms which is always less than the previous proposed GAMDSC in all cases. The difference of simulation time increases more rapidly as the number of sensors is increased. When the number of sensors increased to 500, the performance of algorithm GAMDSC is almost negligible. The less average simulation time means proposed algorithm is much effective for set k-cover problem as compared to GAMDSC, drawback of GA is already discussed above.

Successful Percentage Comparison

Successful percentage is considered as 100% performance in proposed and previous approach. This percentage shows the success in the finding of sets in the set k-cover problems. In above table 5.1 it is shown that the ok% of both algorithms clearly shows that in every case proposed algorithm achieved 100% success from serial 1 to 9 and the previous GAMDSC only got 100% only in one case but we got 0% in all remaining cases from second to last. So, GAMDSC is not suitable for set k-cover problem.

5.7 Comparison of STHGA

At last we compared proposed technique to another previous technique because this technique uses schedule transition operation. In the table 5.2 we showed the results of proposed scheme and Schedule Transition Hybrid Genetic Algorithm (STHGA) [29]. As in above table 5.1 we used same four parameters like named, number of fields formed, Ŧ found, average simulation time and OK percentage using this we compared proposed scheme to the Schedule Transition Hybrid Genetic Algorithm (STHGA). We compared these parameters one by one for the evaluation of both algorithms. Best results of algorithms for each case are shown in bold.

Formed Fields Comparison

We have already discussed above the use of fields and how to forms them. In the above scenario table shows that the results of our proposed scheme better because results greater or at least equal in some cases. In Table 5.1 and Table 2 we can conclude the performance.

Ŧ Comparison

Ŧ is the other parameter that we used to compare our results to previous proposed results whole scheme is dependent on this. Ŧ is the number of disjoint sets of sensors formed in whole area. When compare these T values of proposed algorithm with the STHGA [29] algorithm, which is shown in table 5.1in the column 06 and 11 form serial 01 to 09. Take case 01 and 06 as an example, the number of disjoint complete cover sets formed by our scheme is greater than the STHGA.

In table 5.2 the results are shown, when the number of sensors and sensing ranges are decreased then the number of disjoint sets and the fields formed will also decreases with Ŧ value. So regarding this scenario we come to know that: if we want maximum number of disjoint set we need to increase sensing range rather than increase in the sensors whereas if we increase the number of sensors then there will be increase in the average simulation time which will reduce performance. Finally, we can conclude that if we decrease number of sensors and increase sensing range we can increase performance of whole algorithm that is our main goal.

Average Simulation Time Comparison

The average simulation time of proposed scheme is shown in above table 5.2. Comparisons showed that the average simulation time of algorithms is directly proportional to the number of sensors.

In table 5.2 as the number of sensors increases, the average simulation time also increases. The average simulation time of our proposed scheme is less than the average simulation time of STHGA in all the cases because that ACO is more convergent and fast in the finding of optimal solution as compared to GA. The much less Average simulation time means that the proposed algorithm is much effective for set k-cover problem as compared to STHGA.

Successful Percentage Comparison

The successful percentage field shows that the overall performance of the algorithm in all aspects is successful in finding set k-cover problem. When we compared ok % fields of both the algorithms which is shown in table 5.2 that proposed algorithm and STHGA got 100% success in all the cases.

Table 5.2: Proposed Scheme and STHGA Results

	Cases		ACO					STHGA				
S. No.	N (No. of sensors deployed)	R (sensing ranges)	Nf (No. of fields formed)	T-tilda calculated (Ŧ)	T-tilda - found (Ŧ)	T (Ave. Simulation Time (ms))	ok % (Successful percentage)	Nf (No of fields formed)	T-tilda calculated (Ŧ)	T-tilda-found (Ŧ)	T (Ave. Simulation Time (ms))	ok % (Successful percentage)
1.	100	20	**374**	10	**10**	27.272	100	**385**	7	**7**	33	100
2.	300	15	**674**	14	**14**	312.44	100	**673**	15	**15**	400	100
3.	300	20	**397**	25	**25**	318.95	100	**400**	32	**32**	468	100
4.	400	10	**1563**	8	**8**	625.72	100	**1556**	9	**9**	797	100
5.	400	15	**675**	22	**22**	592.81	100	**676**	22	**22**	767	100
6.	500	8	**2389**	8	**8**	1325.8	100	**2400**	7	**7**	1588	100
7.	500	10	**1580**	12	**12**	1133.4	100	**1586**	15	**15**	11386	100
8.	1000	5	**6043**	5	**5**	3710	100	**6076**	5	**5**	4534	100
9.	1000	8	**2493**	18	**18**	3220	100	**2498**	17	**17**	5901	100
Some of Additional simulations												
10.	120	20	387	16	15	33.15	100	-	-	-	-	-
11.	150	20	395	12	12	90.50	100	-	-	-	-	-
12.	175	20	392	18	18	139.75	100	-	-	-	-	-
13.	200	20	399	21	21	234	100	-	-	-	-	-
14.	250	20	400	22	22	295	100	-	-	-	-	-

5.8 Comparison Of MCMCC

Now we compared our proposed technique to another previous technique MCMCC. In below table 5.3 we showed the results of our scheme and the previous MCMCC [40]. Same as above table 5.1and 5.2 we used same four parameters like named number of fields formed, Ŧ found, average simulation time and OK percentage to compare porposed scheme to the Most Constrained Minimally Constraining Covering (MCMCC) [40]. The best results of both the algorithms for each case are in bold.

Formed Fields Comparison

In the scenario above table results showed that proposed scheme which uses ACO is better because it produced good results.

Table 5.3: Proposed Scheme and MCMCC Results

	Cases		ACO					MCMCC				
S. No.	N (No. of sensors deployed)	R (sensing ranges)	Nf (No. of fields formed)	T-tilda calculated (Ŧ)	T-tilda - found (T)	T (Ave. Simulation Time (ms))	ok % (Successful percentage)		T-tilda Found (Ŧ)		T (Ave. Simulation Time (ms))	
1.	100	20	374	10	10	27.272	100		7		1433	
2.	300	15	674	14	14	312.44	100		15		33922	
3.	300	20	397	25	25	318.95	100		32		44047	
4.	400	10	1563	8	8	625.72	100		9		54844	
5.	400	15	675	22	22	592.81	100		22		81766	
6.	500	8	2389	8	8	1325.8	100		7		76296	
7.	500	10	1580	12	12	1133.4	100		15		124922	
8.	1000	5	6043	5	5	3710	100		5		263469	
9.	1000	8	2493	18	18	3220	100		17		683890	

Ŧ Comparison

Ŧ is used for comparison of base and proposed scheme and gotbetter number of disjoint sets that were equal to the Ŧ. When we compared these Ŧ values of our proposed algorithm with the MCMCC algorithm the values of Ŧ of proposed approach were found to be better to MCMCC [40].

Average Simulation Time Comparison

Microsecond (ms) is used to measure the performance of proposed scheme. When we compared the average simulation time of our scheme and MCMCC, We come to know that our scheme performed better as shown table 5.3.

Successful Percentage Comparison

The successful percentage field represents the better performance of proposed technique as it got 100% in all the aspects of finding the set k-cover problem.

5.9 Results in Graphical Forms

First, we explained our results in tabular form and compared to the previous techniques. Now we are going to explain and compare the produce results to the other previous schemes using graphs.

5.9.1 Proposed Scheme Results

- **Relationship between sensors and disjoint sets**

Graph 5.1 shown relationships between the sensors and disjoint sets. It is clearly shown that if we increase the number of sensors it directly affects disjoint sets. More number of sensors means more numbers of disjoint sets.

The main reason is that when we increase the number of sensors in the target area, it automatically increases the number of fields, which can directly increase the number of disjoint sets of sensors. The increase in number of sensors is effective only up to specific limit, after that limit there is no effect of increase in disjoint sets, because number of fields does not increase.

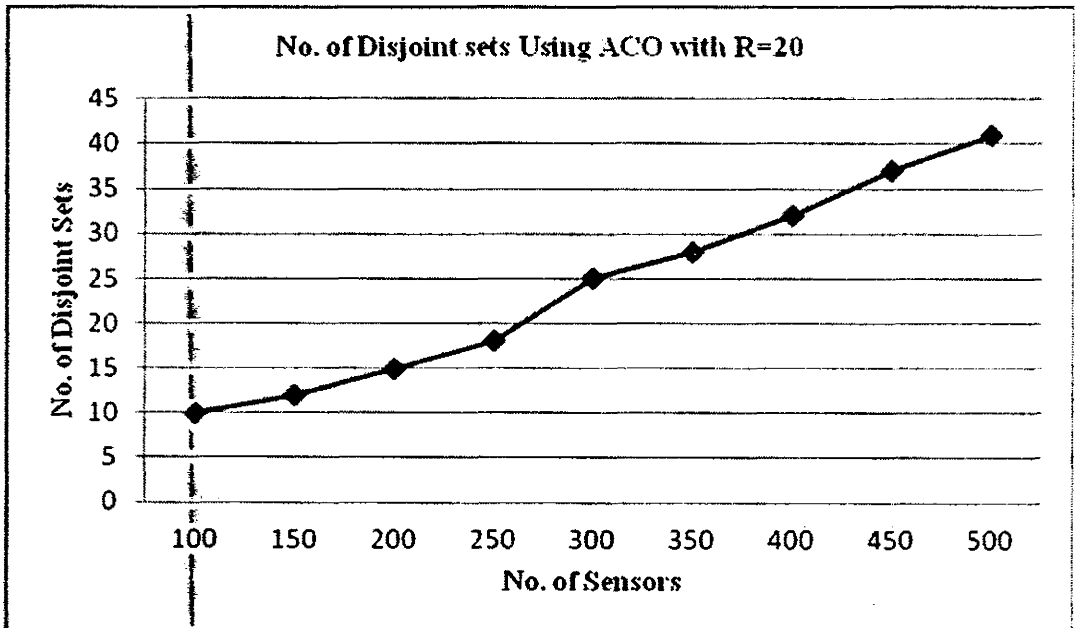

Fig. 5.1: Sensors and Disjoint Sets Relationship

- **Relationship between time and disjoint sets**

Graph 5.2 shows the average simulation time of the algorithm and disjoints sets. When the average simulation time increases, the number of disjoint complete cover sets increases and when the number of pre-calculated disjoint sets of sensors is found simulation time does not increase the number of disjoint complete cover sets. It is easy to make the disjoint sets of sensors at initial stage of algorithm and become more difficult to make more disjoint as the time passes because the more number of redundant sensors are available in the initial stage but as the time passes away these redundant sensors are moved to the complete cover sets. So, less number of redundant sensors is available for in complete cover sets and algorithm takes more and more time to find that redundant sensors for incomplete cover set.

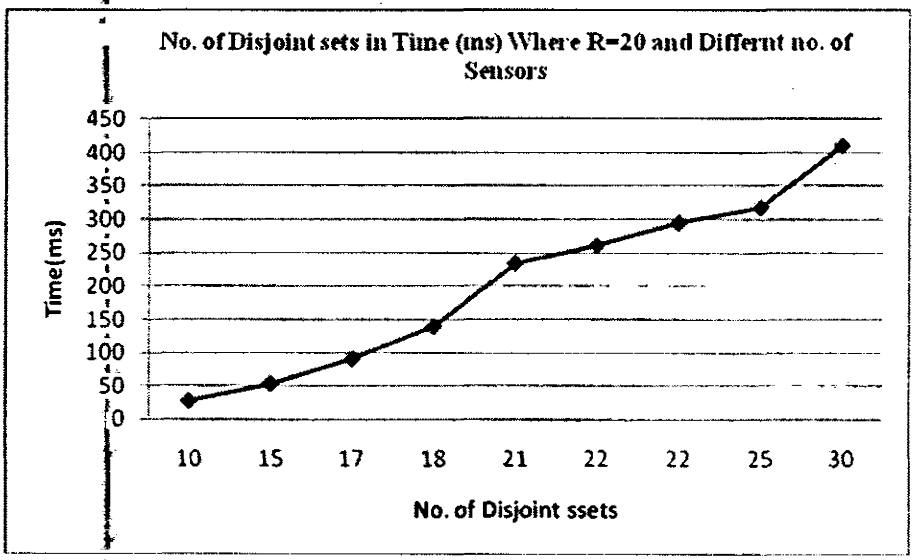

Fig. 5.2: Time and Disjoint Sets Relationship

- **Relationship between sensing ranges and disjoint sets**

Graph 5.3 shows the relationship between sensing ranges of sensors and the number of complete cover sets formed. When we increase the sensing range of the sensors, the number of disjoint complete cover sets increases because of increasing number of formed fields. We observed that when the sensing range of sensors increases, it cover more grids and hence make more fields which means more number of disjoint cover sets. But this concept is true only for a specific sensing range limit. If we closely observe the graph, it can be seen easily that a suitable sensing range is required for disjoint sets. In the beginning when the sensing range is between 2 to 6 there is only 1 to 20 disjoint sets of sensors, but as the sensing range increases from 6 to above the numbers of disjoint sets increases rapidly as in the graph 5.3.When sensing range is increased to 9 the number of disjoint sets increases from 150 to 325 rage. The sensors sensing range also energy dependent which affect the range too. With a high power transceiver se a sensor can coverer wide sensing area. .Due to the requirement of wide sensing area, sensors are not suitable for energy deficient sensors networks.

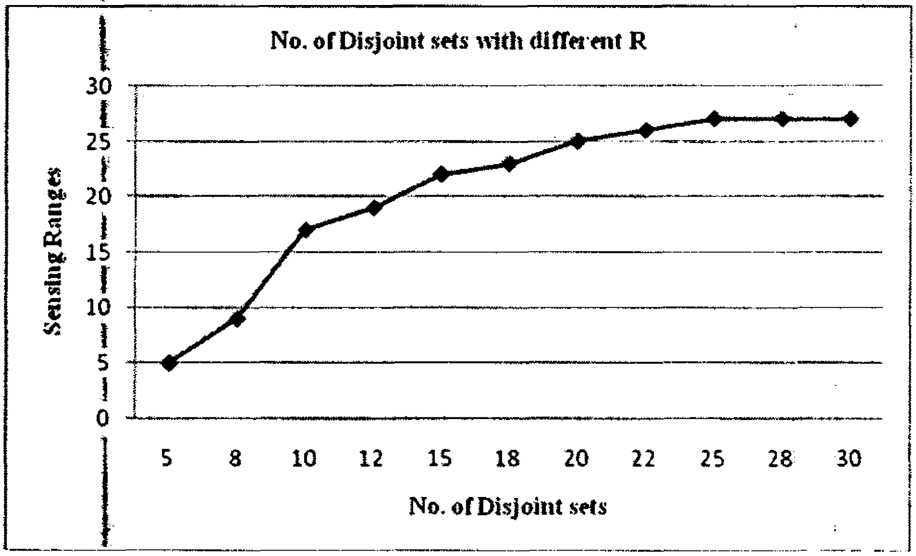

Fig. 5.3: Sensing Ranges and Disjoint Sets Relationship

5.10 Existing Schemes Comparisons

We compared our results with existing schemes and found that the proposed scheme perform in a very reasonable way. In these comparisons at first proposed scheme is evaluated regarding performance with Maximum Disjoint Set Covers (GAMDSC) [28] with different scenarios and secondly with Schedule Transition Hybrid Genetic Algorithm (STHGA) [29] the final comparison was with Most Constrained Minimally Constraining Covers (MCMCC) [40].

5.10.1 GAMDSC Comparisons

Graph 5.4 shows the accordance of number of complete disjoint cover sets of found sensors to the target area deployed sensors for the Maximum Disjoint Set Covers (GAMDSC) [28] and to proposed scheme of ACO. In GAMDSC when the number of sensors increases the number of disjoint complete cover sets increases but it can be seen clearly in graph that GAMDSC is slow as compared to proposed scheme because of slow convergence of GA as compared to proposed scheme ACO.

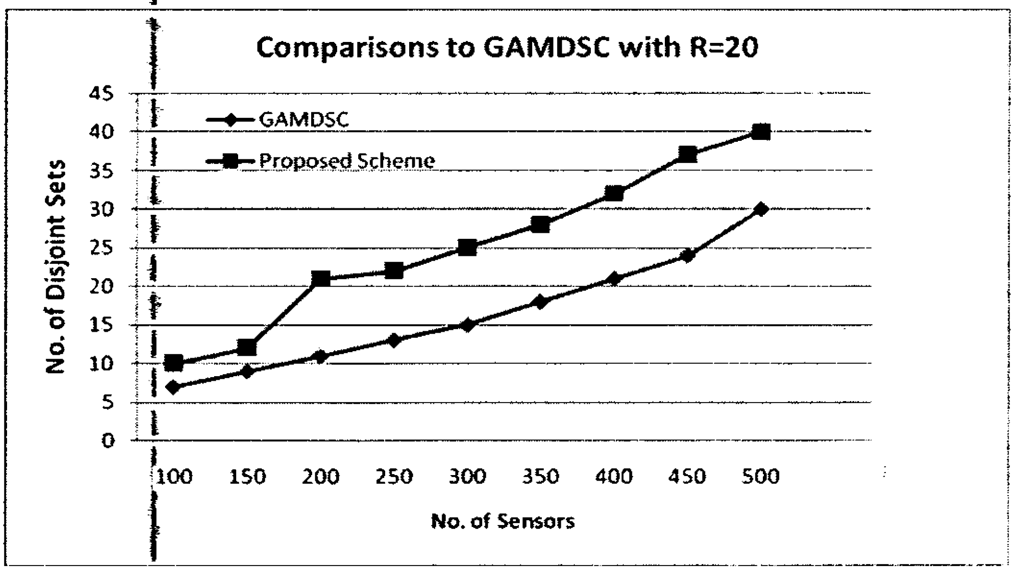

Fig. 5.4: Sensors and Disjoint Sets Relationship

In the graph 5.5 the relation of average simulation time and the number of complete cover sets is presented of GAMDSC and proposed ACO scheme. The performance shown that the GAMDSC algorithm works efficiently in the early stages when there are less number of sensors. But as the number of sensors increases the performance of the algorithm decreases because of a main drawback of GAMDSC in which genetic algorithm is use. Whereas GA is slow in convergence for large scale sensors network and produce small results while using large amount of data.

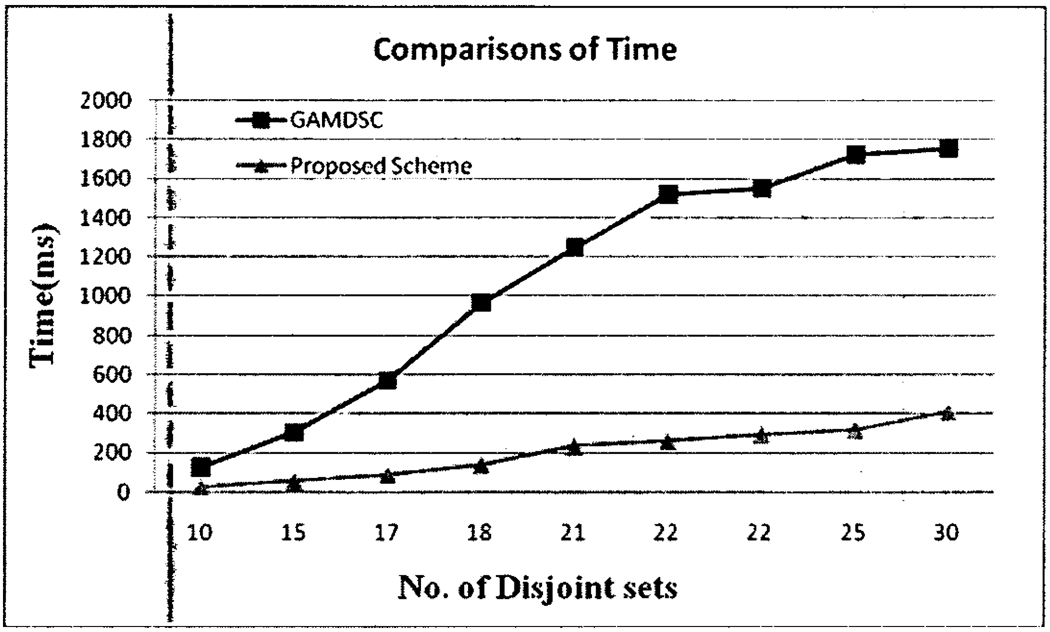

Fig. 5.5: Relationship between time and number of disjoint sets

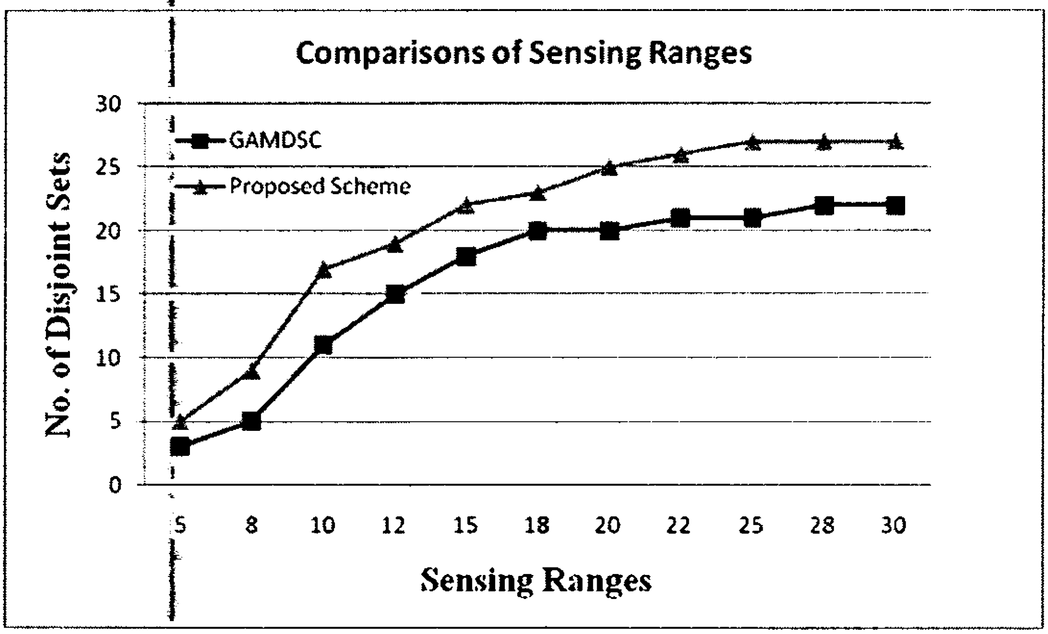

Fig. 5.6: Sensing Ranges and Disjoint Sets Relationship

The graph 5.6 is showing the sensing ranges of the sensors and their effect on number of disjoint complete cover sets formed. The number of disjoint complete cover sets increases as the sensors sensing range increases but this ratio is low when we compared it with proposed scheme. Proposed scheme makes large number of sets when there is increase in sensors sensing range as compared to GAMDSC [28].

The numbers of fields formed by the proposed approach are higher as compared to the GAMDSC. So the comparisons results of proposed scheme are better than the GAMDSC scheme.

5.10.2 STHGA Comparisons

Graph 5.7 shows the relation between number of complete disjoint cover sets of sensors found and number of sensors deployed in target area for the STHGA algorithm [29] and proposed scheme. In case of STHGA the number of sensors increases, the number of disjoint complete cover sets increases. In graph it can clearly see that STHGA is slow as compared to proposed scheme. This could be due to the slow convergence of GA towards the optimal solution.

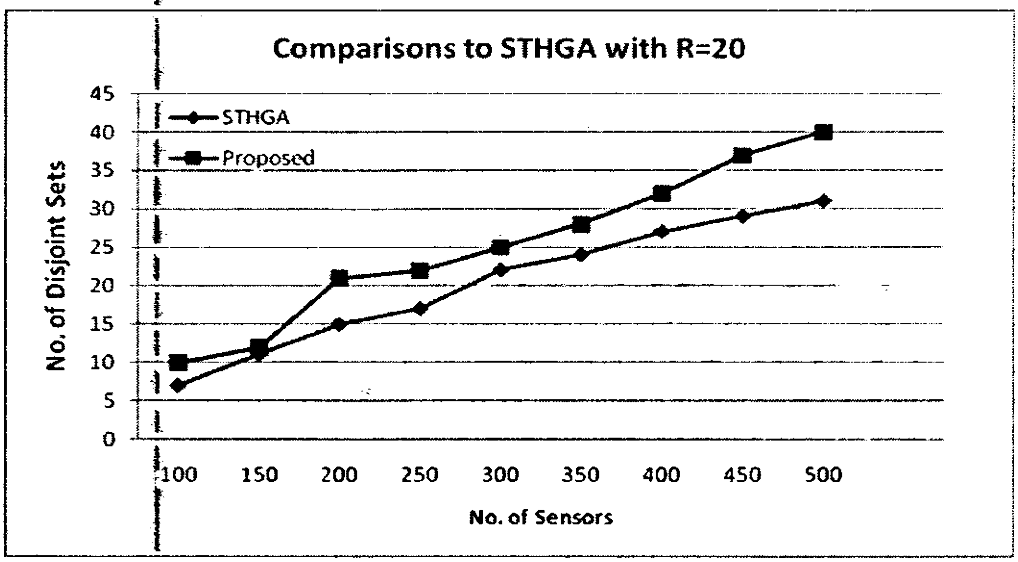

Fig. 5.7: Sensors and Disjoint Sets Relationship

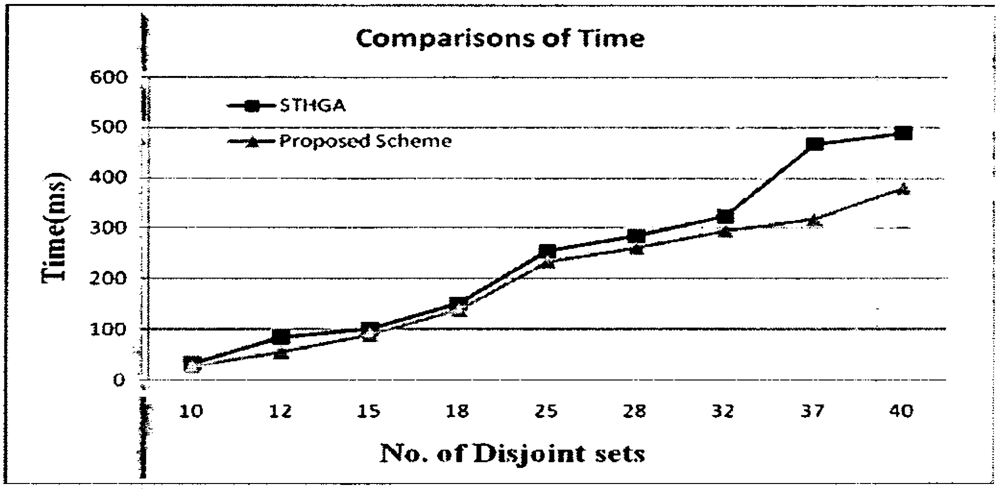

Fig. 5.8: Time and Disjoint Sets Relationship

Graph 5.8 represents average simulation time and the number of complete cover sets found with the passage of simulation time of the STHGA and proposed scheme. The performance can be noticed that the STHGA algorithm works efficiently in the beginning stage when there is less number of sensors. But when as the number of sensors increases the performance of the algorithm decreases.

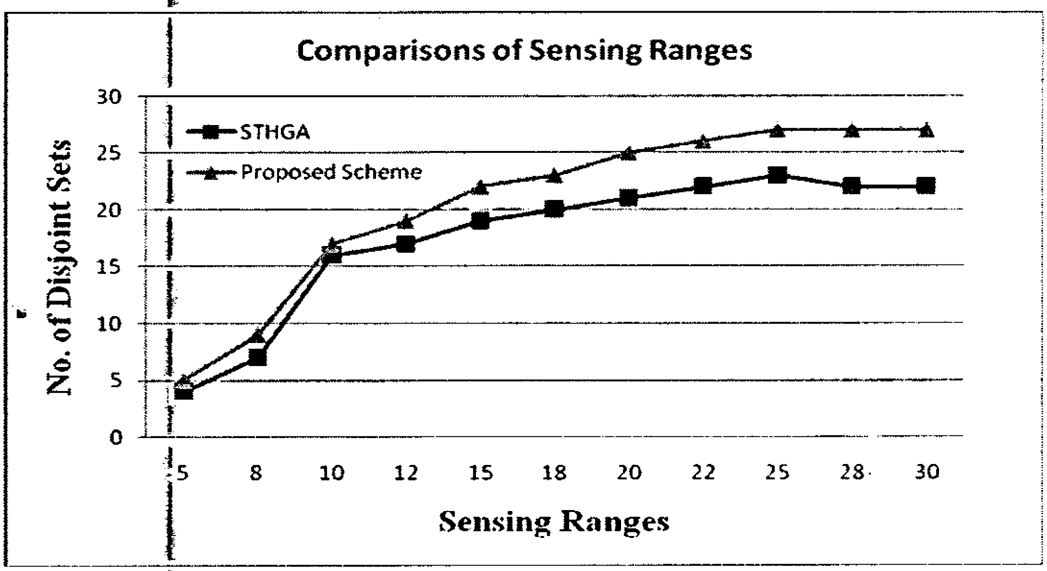

Fig. 5.9: Sensing Ranges and Disjoint Sets Relationship

The graph 5.9 shows the sensors sensing ranges and their effect on number of disjoint complete cover sets formed. The number of disjoint complete cover sets increases as the sensors sensing range increases but this ratio is low when we compared with proposed scheme. Proposed approach makes large number of sensors when there is increase in sensors sensing range as compared to STHGA [29]. So the comparisons results of proposed scheme are better than the STHGA scheme.

5.10.3 MCMCC Comparisons

Graph 5.10 shows the disjoint cover sets of sensors and number of sensors deployed in target area for the MCMCC algorithm [40] and comparison with proposed scheme. In MCMCC the number of sensors increases, the number of disjoint complete cover sets increases and some time decrease. And it is shown in the graph that MCMCC is slow as compared to proposed scheme using ACO.

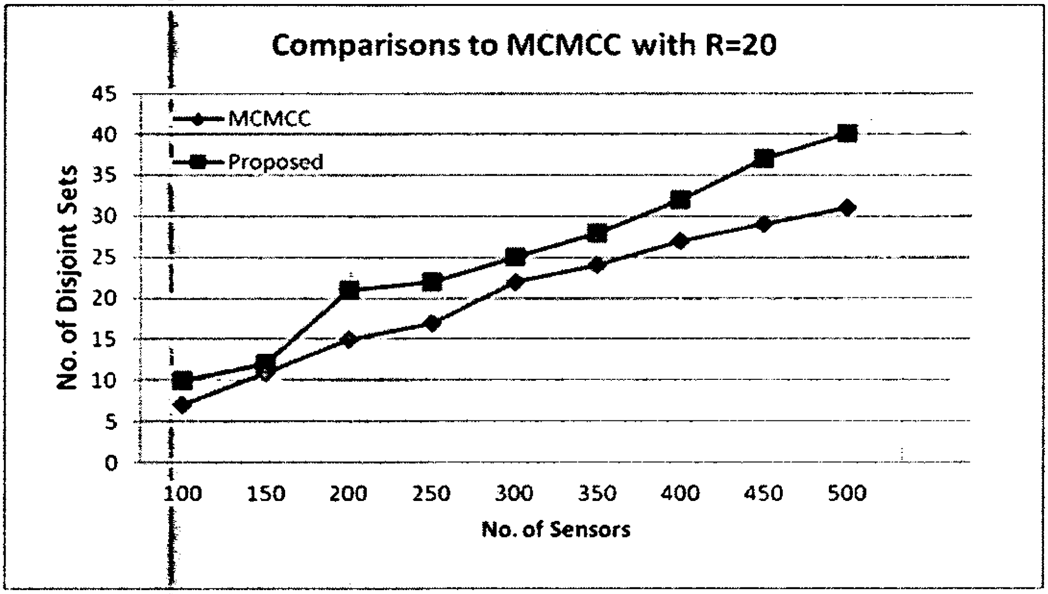

Fig. 5.10: Sensors and Disjoint Sets Relationship

Graph 5.11 shows the average simulation time and the number of complete cover sets found with respect to the simulation time of the MCMCC and proposed scheme. The performance can be noticed that the MCMCC algorithm works efficiently in the beginning stage. MCMCC take much time when there are minimal numbers of sensors but with the growth of number sensors the performance of the algorithms particularly more decrease.

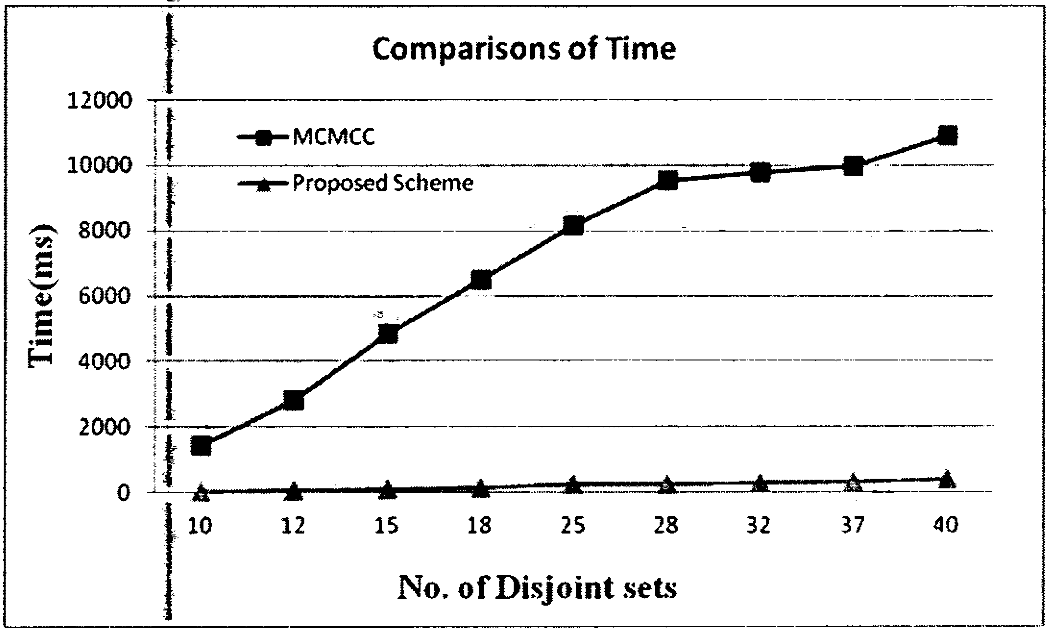

Fig. 5.11: Time and Disjoint Sets Relationship

MCMCC take much time as compared to previously proposed schemes [28]-[29] then our proposed scheme. In the light of the previously mention factors , comparisons and detail discussion of data we can say that the comparisons results of proposed scheme are better than Maximum Disjoint Set Covers (GAMDSC) [28], Schedule Transition Hybrid Genetic Algorithm (STHGA) [29] and Most Constrained Minimally Constraining Covers (MCMCC) [40].

5.11 Benefits of Proposed Approach

In proposed scheme we used the ACO algorithm instead of Genetic Algorithm in WSN disjoint sets finding problem and increase the lifetime of wireless sensors networks. The beauty of proposed algorithm is that it uses previously gathered information that is in the form of pheromone updating to move further and further for an optimum solution. In contrast, the genetic algorithm creates chromosomes on random bases that are not even sure to get better fitness results. We found that proposed ACO algorithm takes comparatively less time in finding of disjoint sets, better in average simulation time as compared to our base paper. There are three approaches GAMDSC [28], STHGA [29] and MCMCC [40] used in our base papers, they requires more calculations but produces less efficient results in term of time and are much coasty regarding sensor's battery power. In contrast to the others approaches as proposed approach performed very low calculations to producing efficient results. Our proposed approach play vital role in increasing the lifetime of sensor nodes and of whole network as it reduces communication for finding sets.

Chapter 6 Conclusion and Future Work

6.1 Conclusions

We proposed new approach to find maximum number of disjoint cover sets the whole area by using Ant Colony Optimization method. We found disjoint sets that are further used to cover the whole area one by one and this process enhance the lifetime of wireless sensors networks.

Its distinct features and importance concluded as follows:

The advantage of proposed algorithm in solving the disjoint set covers problems lies in it's with the adoption of schedule transition operations and some well-designed operations. These operations were very suitable for finding the maximum number of disjoint complete cover sets for maximizing the lifetime of WSNs and enhancing the performance of our proposed scheme. The schedule transition operations were very helpful to reduce the average simulation time. The ACO operations and schedule transition operations cooperate to search for the best scheduling scheme of sensors. In particular, the usage of redundancy information among the scheduled sensors has been shown to be efficient in this work.

Proposed algorithm is applicable to both point-coverage and area-coverage problems in WSNs for finding disjoint sets. The area coverage problems are more difficult than point coverage problems, because area-coverage problems involve complete area instead of only a few target points as were in point-coverage problems, the proposed algorithm achieved high-quality solutions in a efficient way and outperform the other previous proposed schemes[28]-[29] and [40].

6.2 Future Work

Although proposed algorithm works well all most in every test case yet it still require to be improve further for more better performance. When the problem becomes more complicated, the time consumed to find the better solution increases rapidly. For the future work, more restricted heuristic operations should be applied to proposed algorithm, in order to make the algorithm capable for more difficult SET k-cover problems.

Further application of the proposed algorithm to other similar problems is an important part of my future research work and to use other hybrid approaches. We shall investigate the application of proposed scheme by considering the energy consumption of sensors using different sensing ranges and will find out the best configuration between different working modes and the lifetime of complete cover sets.

Finally, with the reference of our literature survey we found many other evolutionary methods which may also be used for our problem like fuzzy logic technique. It is a suitable technique less complex in calculation so it could be the one of best replacement of proposed approach.

References

[1] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, E. Cayirci, "Wireless sensor networks: A Survey", IEEE Communication Magazine,August 2002.

[2] H. Y. Shwe, J. Xiao-hong, S. Horiguchi, "Energy saving in wireless sensor networks", Journal of Communication and Computer, vol. 6,no.54, ISSN 1548-7709, USA, May 2009.

[3] C. Z. Zhou, B. Krishnamachari, "Localized topology generation mechanisms for self-configuring sensor networks", in Proc. IEEE Globe-Com, vol. 3, pp. 1269-1273, Dec. 2003

[4] H.Y. Shwe, X.-H. Jiang, S. Horiguchi, "Energy saving in wireless sensor networks", J. Commun. Comput., vol. 6, no. 5, pp. 20–28, May 2009.

[5] M. Younis, K. Akkaya, "Strategies and techniques for node placement in wireless sensor networks: A survey," Ad Hoc Netw., vol. 6, no. 4, pp. 621–655, Jun. 2008.

[6] L. Wang, Y. Xiao,"A survey of energy-efficient scheduling mechanisms in sensor networks," Mobile Netw. Appl., vol. 11, no. 5, pp. 723–740, Oct. 2006.

[7] M. Cardei, D.-Z. Du, "Improving wireless sensor network lifetime through power aware organization", Wireless Netw., vol. 11, no. 3, pp. 333–340, May 2005.

[8] S. Slijepcevic, M. Potkonjak, "Power efficient organization of wireless sensor networks," in Proc. IEEE Int. Conf. Commun., vol. 2. Finland, pp. 472–476, 2001.

[9] C. Liu, K. Wu, Y. Xiao, B. Sun, "Random coverage with guaranteed connectivity: Joint scheduling for wireless sensor networks", IEEE Trans. Parallel Distrib. Syst., vol. 17, no. 6, pp. 562–575, Jun. 2006.

[10] Othman, F. Bouabdallah, N. Boutaba, "Energy conservation in wireless sensor networks: A survey", IEEE Communication Magazine, vol. 40, pp. 1-6., Issue 8. 2009.

[11] Eshghi, A. Toroghi, "Energy Conservation Strategy in Cluster-based Wireless Sensor Networks", International Conference on Advanced Computer Theory and Engineering, pp. 1015-1019, 2008.

[12] YE, F. Zhong, G.LU S. Zhang, L. Peas, "A Robust Energy Conserving Protocol for Long-lived Sensor Networks", In Proc. 23rd Conf. Distributed Computing Systems Los Alamitos, August 2003, pp. 35-41.

[13] YE, F., Zhong, G.LU, S. Zhang, " Energy efficient robust sensing coverage in large sensor networks", Technical report, UCLA, 2002.

[14] Z. Abrams, S. Goel, S. Plotkin "Set K-Cover Algorithms for Energy Efficient Monitoring in Wireless Sensor Networks", IPSN'O4, Berkeley, California, USA, ACM , pp.26-27 April 2004.

[15] P. Berman G. Calinescu, C. Shah, "Power Efficient Monitoring Management in Sensor Networks" , WCNC / IEEE Communications Society, 2004.

[16] M. Cardei ,M. T. Thai, Y. Li, "Energy -Efficient Target Coverage in Wireless Sensor Networks" , IEEE, 2005.

[17] A. Dhawan, C. T. Vu, A. Zelikovsky, Y. Li, S. K. Prasad" Maximum Lifetime of Sensor Networks with Adjustable Sensing Range", Proceedings of the Seventh ACIS International Conference on Software Engineering, Artificial Intelligence, Networking, and Parallel/Distributed Computing (SNPD'06), 2006.

[18] S. Slijepcevic, M. Potkonjak" Power Efficient Organization of Wireless Sensor Networks", IEEE, 2001.

[19] M. Cardei, J. Wu, "Energy-Ef_cient Coverage Problems in Wireless Ad Hoc Sensor Networks", Journal Computer Communications, vol. 29 Issue 4, pp. 413-420, February, 2006.

[20] D. Zorbas, D. Glynos, P. Kotzanikolaou, C. Douligeris, "Solving coverage problems in wireless sensor networks using cover sets" Ad Hoc Networks on ScienceDirect, 27 October 2009.

[21] M. Cardei, J. Wu, "Energy-efficient coverage problems in wireless ad-hoc sensor networks," Comput. Commun., vol. 29, no. 4, pp. 413–420, Feb. 2006.

[22] Cardei, M. DU, D. Z, " Improved wireless sensor network lifetime through power aware organization", *Wireless Networks*, pp. 330-340, 2005.

[23] D. Zorbas, D. Glynos, P. Kotzanikolaou, " Solving coverage problems in wireless sensor networks using cover sets" , Ad Hoc Networks 8, pp.400–415, 2010.

[24] R. Schaefer, "Foundations of Global Genetic Optimization", New York: Springer-Verlag, 2007.

[25] Price, K. V., R. M. Storn , Lampienn, J. A, "Differential Evolution, A Practical Approach to Global Optimization", Natural Computing Series Berlin, Germany: Springer-Verlag, 2005.

[26] Passino, K. M. "Bio mimicry of bacterial foraging for distributed optimization and control", IEEE Control System Mag., vol. 22, no. 3, pp. 52–67, 2002.

[27] M. Dorigo, T. Stutzle, Book Ant Colony Optimization, chapter 2 ,1996-97

[28] C.-C. Lai, C.-K. Ting,R.-S. Ko, "An effective genetic algorithm to improve wireless sensor network lifetime for large-scale surveillance applications," in Proc. IEEE Congr. Evol. Comput., pp. 3531–3538, 2007.

[29] X. Hu, J. Zhang, Y. Yu, "Hybrid Genetic Algorithm Using a Forward Encoding Scheme for Lifetime Maximization of Wireless Sensor Networks", IEEE transactions on evolutionary computation, vol.14, no.5, oct. 2010

[30] Y. d. Valle, G. K. Venayagamoorthy, S. Mohagheghi, "Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems",IEEE transactions on evolutionary computation, vol. 12, no. 2, april 2008.

[31] John, H. Holland. "Adaptation in Natural and Artificial Systems", University of Michigan Press, Ann Arbor, MI, 1975.

[32] Turgut, D. Das, S. K., R. Elmasri, B. Turgut, "Optimizing clustering algorithm in mobile ad hoc networks using genetic algorithmic approach", *IEEE Global Telecom Conference,* vol. 1, pp. 62-66, 2002.

[33] C. Liao, H. Ting, "Extending Wireless Sensor Network Lifetime through Order-Based Genetic Algorithm", IEEE, 2008.

[34] J. Kennedy, R. Eberhart, "Particle swarm optimization", In Proc. IEEE Int. Conf. Neural Network, vol. 4, pp. 1942–1948, 1995.

[35] V. Raghavendra, G. Kumar, "Particle Swarm Optimization in Wireless Sensor Networks", IEEE Transactions on systems, MAN, and cybernetics part c: applications and reviews, vol. 41, no. 2, 2011.

[36] M. Dorigo, C. Blum," Ant colony optimization theory: A survey", Theoretical Computer Science , DirectScience 344, pp.243 – 278, 30 May 2005.

[37] R. Putha, L. Quadrifoglio, E. Zechman "Comparing Ant Colony Optimization and Genetic Algorithm Approaches for Solving Traffic Signal Coordination under Oversaturation Conditions " ,Computer-Aided Civil and Infrastructure Engineering 27 USA , pp.14–28, 2012.

[38] N. B. Sariff, N. Buniyamin "Comparative Study of Genetic Algorithm and Ant Colony Optimization Algorithm Performances for Robot Path Planning in Global Static

Environments of Different Complexities" University Technology Mara (UiTM), Shah Alam, Selangor, 40450 MALAYSIA, pp.132 - 137,August 30, 2009.

[39] K. Chakrabarty, S. S. Iyengar, H. Qi, E. Cho, "Grid coverage for surveillance and target location in distributed sensor networks,"IEEE Trans. Comput., vol. 51, no. 13, pp. 1448–1453, Dec. 2002

[40] S. Slijepcevic, M. Potkonjak, "Power efficient organization of wireless sensor networks," in Proc. IEEE Int. Conf. Commun., vol. 2, pp. 472–476, 2001.