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AN EFFICIENT ALGORITHMIC APPROACH FOR MULTICAST SCHEDULING USING ANT COLONY OPTIMIZATION

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Abstract**—** Multicasting is one of the prominent that is used in the networks for the transmission of data packets. In this scheduling technique, the packets are transferred erratically across the distributed network. The convey of packets randomly across network cases the anonymous users to access the packets. The data packets should be transferred in authorized path to multiple recipients. The main objective of this research work is to transfer packets to the destination through optimized path. It can be achieved using the assorted metaheuristic techniques including genetic algorithm, simulated annealing, honey bee algorithm and many others. We have used Ant Colony Optimization for solving the optimization problem. An authorized and novel technique is proposed to overcome these problems. In the classical or traditional system, they are mainly concentrated on transferring packets between the source and destination and also they are concentrated when the source and destination are under movement, nowadays the mobile devices plays major role in network topology. Multicasting was clearly proved in the classical system by transferring packets from one source to many destinations on a single time. The proposed system is designed to overcome various problems, arises during the multicast packet transfer to the mobile nodes. The proposed system provides an optimized route to the various destinations using the ant algorithm as we discussed above, with the help of this path the packets are transferred to the various destinations. In this multicast scheduling technique, various problems arising during the routing has been overcome by using Ant algorithm whereby the proposed novel technique provides solution for routing for nodes which are static and nodes under movement.

Keywords— Multicasting,ACO

I. *INTRODUCTION*

1.1Intelligence

Swarm intelligence (SI) is the collective behavior of decentralized, self-organized systems, natural or artificial. The concept is employed in work on artificial intelligence. The expression was introduced by Gerardo Beni and Jing Wang in 1989, in the context of cellular robotic systems [9].

SI systems are typically made up of a population of simple agents or boids interacting locally with one another and with their environment. The inspiration often comes from nature, especially biological systems. The agents follow very simple rules, and although there is no centralized control structure dictating how individual agents should behave, local, and to a certain degree random, interactions between suc The definition of swarm intelligence is still not quite clear. In principle, it should be a multi-agent system that has self-organized behavior that shows some intelligent behavior.

The application of swarm principles to robots is called swarm robotics, while 'swarm intelligence' refers to the more general set of algorithms. 'Swarm prediction' has been used in the context of forecasting problems.

1.2EXAMPLES

Ant colony optimization : Ant colony optimization (ACO) is a class of algorithms modeled on the actions of an ant colony. ACO methods are useful in problems that need to find paths to goals. Artificial 'ants'—simulation agents—locate optimal solutions by moving through a parameter space representing all possible solutions. Natural ants lay down pheromones directing each other to resources while exploring their environment. The simulated 'ants' similarly record their positions and the quality of their solutions, so that in later simulation iterations more ants locate better solutions. [10]

Artificial bee colony algorithm : Artificial bee colony algorithm (ABC) is a metaheuristic algorithm introduced by Karaboga in 2005 [11], and simulates the foraging behavior of honey bees. The ABC algorithm has three phases: employed bee, onlooker bee and scout bee. In the employed bee and the onlooker bee phases, bees exploit the sources by local searches in the neighbourhood of the solutions selected based on deterministic selection in the employed bee phase and the probabilistic selection in the onlooker bee phase. In the scout bee phase which is an analogy of abandoning exhausted food sources in the foraging process, solutions that are not beneficial anymore for search progress are abandoned, and new solutions are inserted instead of having them explore other regions in the search space.

Backtracking search optimization algorithm : Backtracking search optimization algorithm (BSA) is a swarm-based evolutionary algorithm (EA) for solving real-valued numerical optimization problems. The problem solving success of BSA was compared to the successes of PSO, CMAES, ABC, JDE, CLPSO and SADE in 2013 [12].

Differential search algorithm : Differential search algorithm (DSA) has been inspired by migration of superorganisms. DSA is utilizing the concept of brownian like motion. The problem solving success of DSA was compared to the successes of ABC, JDE, JADE, SADE, EPSDE, GSA, PSO2011 and CMA-ES algorithms for solution of numerical optimization problems in 2012 [13].

Intelligent Water Drops algorithm : Intelligent water Drops (IWD) algorithm is a nature-inspired swarm-based optimization algorithm, which was first introduced in 2007. The IWD algorithm attempts to mimic the behavior of natural water drops in rivers. Here, the soil is the quantity that is carried by each artificial water drop in the algorithm. Several versions of the IWD algorithm have been suggested for different applications [14].

Multi-swarm optimization : Multi-swarm optimization is a variant of particle swarm optimization (PSO) based on the use of multiple sub-swarms instead of one (standard) swarm. The general approach in multi-swarm optimization is that each sub-swarm focuses on a specific region while a specific diversification method decides where and when to launch the sub-swarms. The multi-swarm framework is especially fitted for the optimization on multi-modal problems, where multiple (local) optima exist.

Particle swarm optimization : Particle swarm optimization (PSO) is a global optimization algorithm for dealing with problems in which a best solution can be represented as a point or surface in an n-dimensional space. Hypotheses are plotted in this space and seeded with an initial velocity, as well as a communication channel between the particles [17, 18]. Particles then move through the solution space, and are evaluated according to some fitness criterion after each timestep. Over time, particles are accelerated towards those particles within their communication grouping which have better fitness values. The main advantage of such an approach over other global minimization strategies such as simulated annealing is that the large number of members that make up the particle swarm make the technique impressively resilient to the problem of local minima.

1.3APPLICATIONS

Swarm Intelligence-based techniques can be used in a number of applications. The U.S. military is investigating swarm techniques for controlling unmanned vehicles. The European Space Agency is thinking about an orbital swarm for self-assembly and interferometry. NASA is investigating the use of swarm technology for planetary mapping. A 1992 paper by M. Anthony Lewis and George A. Bekey discusses the possibility of using swarm intelligence to control nanobots within the body for the purpose of killing cancer tumors [19]. Conversely al-Rifaie and Aber have used Stochastic Diffusion Search to help locate tumours. Swarm intelligence has also been applied for data mining [20].

1.3.1ANT-BASED ROUTING

The use of Swarm Intelligence in Telecommunication Networks has also been researched, in the form of Ant Based Routing. This was pioneered separately by Dorigo et al. and Hewlett Packard in the mid-1990s, with a number of variations since. Basically this uses a probabilistic routing table rewarding/reinforcing the route successfully traversed by each "ant" (a small control packet) which flood the network. Reinforcement of the route in the forwards, reverse direction and both simultaneously have been researched: backwards reinforcement requires a symmetric network and couples the two directions together; forwards reinforcement rewards a route before the outcome is known (but then you pay for the cinema before you know how good the film is). As the system behaves stochastically and is therefore lacking repeatability, there are large hurdles to commercial deployment. Mobile media and new technologies have the potential to change the threshold for collective action due to swarm intelligence (Rheingold: 2002, P175).

The location of transmission infrastructure for wireless communication networks is an important engineering problem involving competing objectives. A minimal selection of locations (or sites) are required subject to providing adequate area coverage for users. A very different ant inspired swam intelligence algorithm, Stochastic diffusion search (SDS), has been successfully used to provide a general model for this problem, related to circle packing and set covering. It has been shown that the SDS can be applied to identify suitable solutions even for large problem instances [21].

Airlines have also used ant-based routing in assigning aircraft arrivals to airport gates. At Southwest Airlines a software program uses swarm theory, or swarm intelligence—the idea that a colony of ants works better than one alone. Each pilot acts like an ant searching for the best airport gate. "The pilot learns from his experience what's the best for him, and it turns out that that's the best solution for the airline," Douglas A. Lawson explains. As a result, the "colony" of pilots always go to gates they can arrive at and depart from quickly. The program can even alert a pilot of plane back-ups before they happen. "We can anticipate that it's going to happen, so we'll have a gate available," Lawson says [22].

1.3.2CROWD SIMULATION

Artists are using swarm technology as a means of creating complex interactive systems or simulating crowds.

Stanley and Stella in: Breaking the Ice was the first movie to make use of swarm technology for rendering, realistically depicting the movements of groups of fish and birds using the Boids system. Tim Burton's Batman Returns also made use of swarm technology for showing the movements of a group of bats. The Lord of the Rings film trilogy made use of similar technology, known as Massive, during battle scenes. Swarm technology is particularly attractive because it is cheap, robust, and simple.

Airlines have used swarm theory to simulate passengers boarding a plane. Southwest Airlines researcher Douglas A. Lawson used an ant-based computer simulation employing only six interaction rules to evaluate boarding times using various boarding methods.(Miller, 2010, xii-xviii) [23].

1.3.3SWARMIC ART

In a series of works al-Rifaie [23] et al have successfully used two swarm intelligence algorithms – one mimicking the behavior of one species of ants (Leptothorax acervorum) foraging (Stochastic diffusion search (SDS)) and the other algorithm mimicking the behavior of birds flocking (Particle swarm optimization PSO) – to describe a novel integration strategy exploiting the local search properties of the PSO with global SDS behavior. The resulting hybrid algorithm is used to sketch novel drawings of an input image, exploliting an artistic tension between the local behavior of the 'birds flocking' - as they seek to follow the input sketch - and the global behavior of the 'ants foraging' - as they seek to encourage the flock to explore novel regions of the canvas. The 'creativity' of this hybrid swarm system has been analysed under the philosophical light of the 'rhizome' in the context of Deleuze's well known 'Orchid and Wasp' metaphor.

Swarm intelligence-related concepts and references can be found throughout popular culture, frequently as some form of collective intelligence or group mind involving far more agents than used in current applications.

1.4ANT COLONY OPTIMIZATION : DETAILED IMPLEMENTATION ISSUES AND RELATED ASPECTS

Ant colony optimization (ACO) [1] is one of the most recent techniques for approximate optimization. The inspiring source of ACO [1] algorithms are real ant colonies. More importantly, ACO is inspired by the ants' foraging behavior. At the core of this behavior is the indirect communication between the ants by means of organic pheromone trails, which enables them to select the short paths between their nest and food sources.

A complex task cannot be performed by a single ant, but a group of ants can make even a complex task into simpler ones. Ant colony optimization technique is used to provide fair resolution to the various optimization problems. In this optimization technique moving man-made ants are really helpful in providing solutions by impersonating the real ants, dump fake pheromone on the graph so that the future man-made ants can provide even better solution to these problems.

In the natural world, ants (initially) wander randomly, and upon finding food return to their colony while laying down pheromone trails. If other ants find such a path, they are likely not to keep travelling at random, but to instead follow the trail, returning and reinforcing it if they eventually find food.

Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and positive feedback eventually leads to all the ants' following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

Ant colony optimization algorithms have been applied to many combinatorial optimization problems, ranging from quadratic assignment to protein folding or routing vehicles and a lot of derived methods have been adapted to dynamic problems in real variables, stochastic problems, multi-targets and parallel implementations. It has also been used to produce near-optimal solutions to the travelling salesman problem. They have an advantage over simulated annealing and genetic algorithm approaches of similar problems when the graph may change dynamically; the ant colony algorithm can be run continuously and adapt to changes in real time. This is of interest in network routing and urban transportation systems.

The first ACO algorithm was called the Ant system and it was aimed to solve the travelling salesman problem, in which the goal is to find the shortest round-trip to link a series of cities. The general algorithm is relatively simple and based on a set of ants, each making one of the possible round-trips along the cities. At each stage, the ant chooses to move from one city to another according to some rules:

1. It must visit each city exactly once;
2. A distant city has less chance of being chosen (the visibility);
3. The more intense the pheromone trail laid out on an edge between two cities, the greater the probability that that edge will be chosen;
4. Having completed its journey, the ant deposits more pheromones on all edges it traversed, if the journey is short;
5. After each iteration, trails of pheromones evaporate

1.6IMPLEMENTATION OF ANT COLONY OPTIMIZATION ALGORITHM

In an ant colony, the ants sorted their foods and larvae in consistent heaps. There are several steps helpful solving the optimization problems in WSN.

- The platform is a two dimensional lattice
- The mobile sensor nodes are sprinkled on the lattice
- The artificial ants are developed in such a way that automatically leap from one node to the another node
- Each and every node has ability to change the colour of the mobile sensor node in accordance with the perspective rules.
- This perspective rule requires only local values as the input.

The mobile sensor nodes are coloured, re-coloured or made colourless by a mechanism which take local data as an input. The constriction on colouring the node depends on type of node and its cluster capability.

The **probability** $P(d)$ of discolouring a mobile sensor node A, is denoted as follows

$$P(d) = (Cd/(Cd + fa(x)))^2$$

x=number of exclusive neighbour

Cd=constant

$fa(x)$=local density function related to node A

The **probability** $P(r)$ of re colouring a mobile sensor node A, increases with number of similar coloured nodes in the neighbourhood.

$$P(r) = (fa(x)/(Cr + fa(x)))^2$$

Cr=constant

$fa(x)$=local density function related to node A

The probability of untouched nodes $P(U)$

$$P(U) = 1 - (P(d) + P(r))$$

It is used to estimate the traffic overhead of the mobile sensor node A.

Benefits

- This algorithm helps in the reduction of IP header size
- It reduces the transmission power to reach the cluster heads in WSN.
- Nodes registered with more than one group acts as a bridge for providing many paths with fault tolerance capacity.

Chapter 6

Results and Discussions

5.1Simulation Set up

The upcoming snapshots represent the wireless sensor network while transferring packets

EXISTING TECHNIQUE CASE 1

Fig 10 : Initial position of node

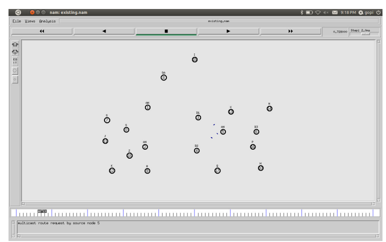

Fig 11:Multicast route request

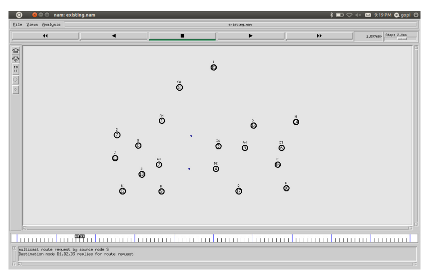

Fig :route reply

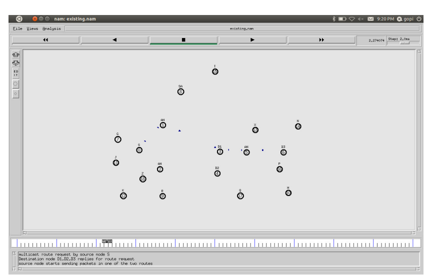

Fig 12: packet transfer

EXISTING SYSTEM CASE 2

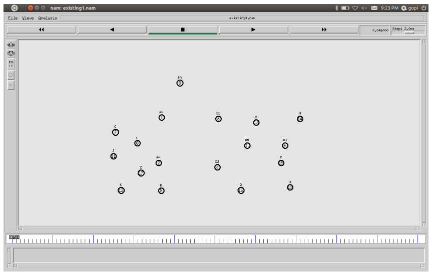

Fig 13: Initial position of node

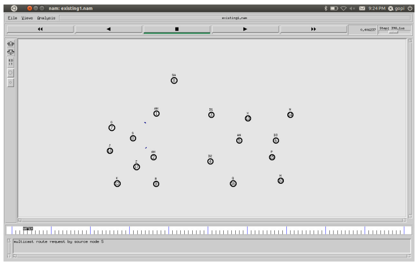

Fig 14: Route request by source node

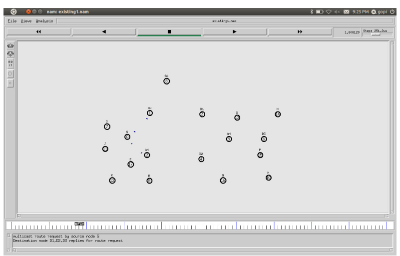

Fig 15: Route reply by destination node

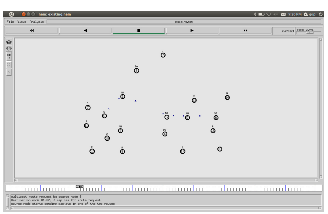

Fig16 :Packet transfer to the destination node

PROPOSED SYSTEM CASE 1

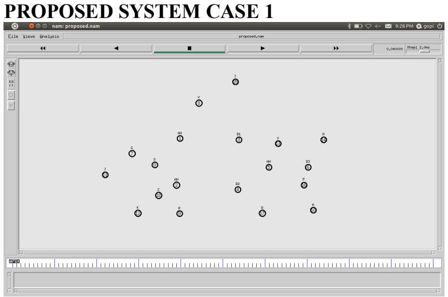

Fig 17:initial position of nodes

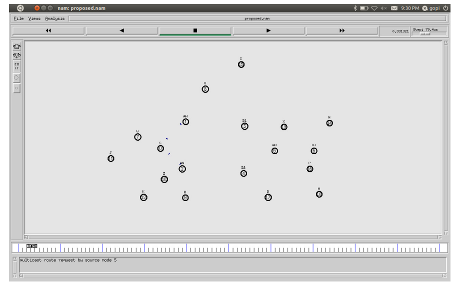

Fig 18:Route Request By Source Node

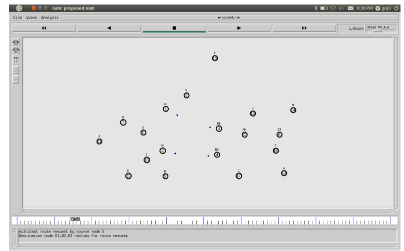

Fig 19:Route Reply From Destination

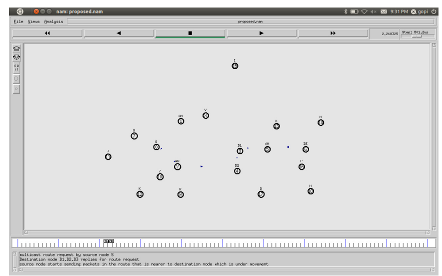

Fig 20:Packet Transfer To Destination

PROPOSED SYSTEM CASE 2

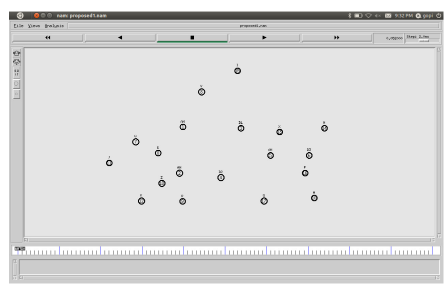

Fig 21: Initial Position Of Node

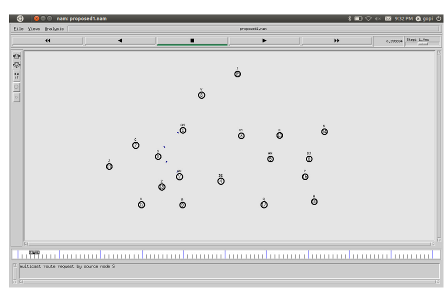

Fig 22 :Route Request By Source Node

Scenarios	Time (in seconds)	Packet drop (in count)
Existing system 1	9.2	29
Existing system 2	9.2	5
Proposed system 1	9.2	2
Proposed system 2	9.2	2

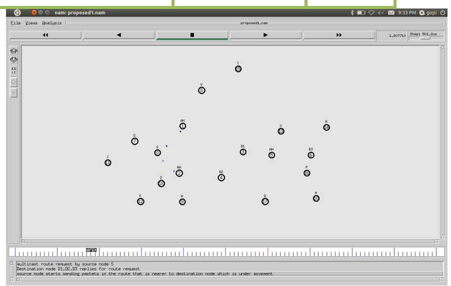

Fig 23:Route Reply From Destination Node

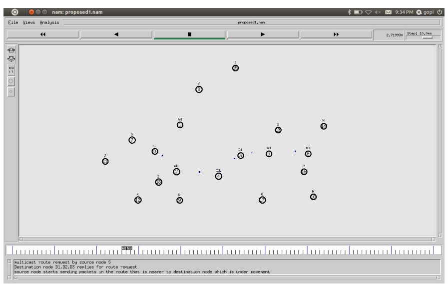

Fig 24:Packet Transfer By Source Node To Destination

PACKET LOSS COMPARISON

Table 1:Packet Loss Comparison

PACKET LOSS COMPARISON GRAPH BAR GRAPH

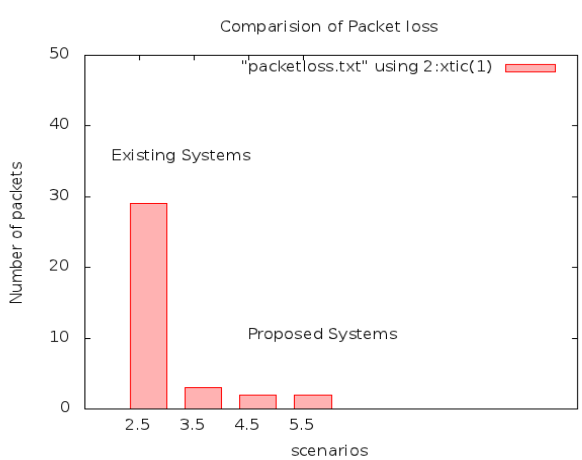

Fig 25: Packet Loss Comparison Bar Graph

XGRAPH

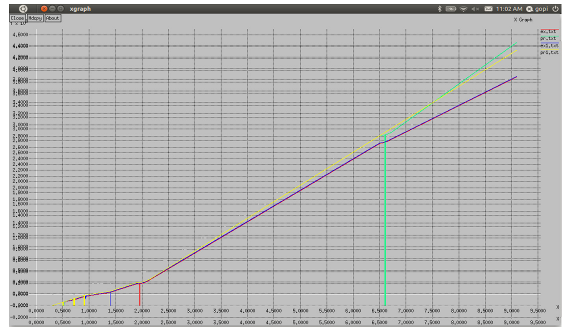

Fig 26: Packet Transfer Rate X Graph

DATA RATE GRAPH

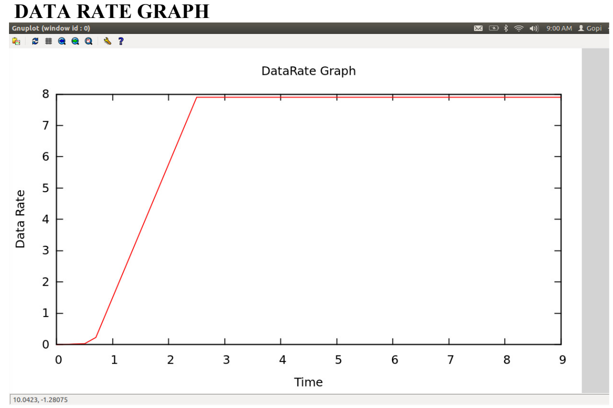

Fig 27: Data Rate Transfer X Graph

In base paper, the graph data rate is nearly 6kbps but in our approach the transfer rate is up to 8kbps.

PACKET DELAY GRAPH

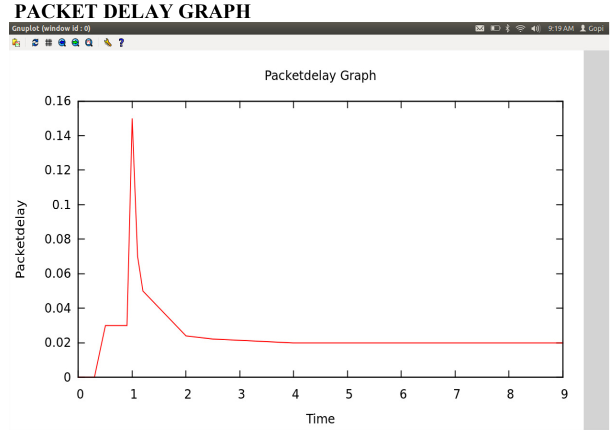

Fig 25: Packet Delay Transfer Rate X Graph

In base paper the packet delay rate is approximately 0.048 m/s, but in our approach it is nearly 0.02 m/s.

PACKET RECEIVING RATE GRAPH

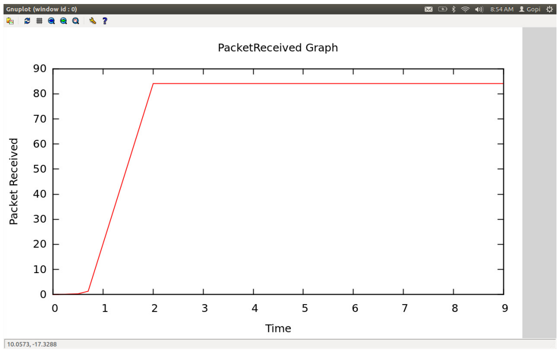

Fig 28: Packet Received Transfer Rate X Graph

In base paper packet receiving rate is nearly 70kbps, in our approach it is about 81kbps.

PACKET LOSS GRAPH

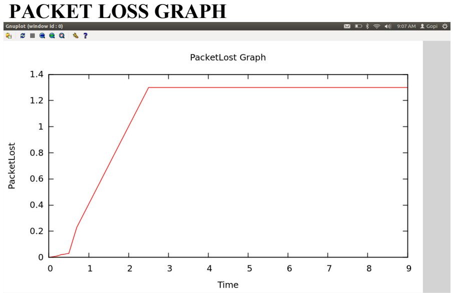

Fig 29: Packet Loss Transfer Rate X Graph

In the base paper the packet loss rate is average 2 kbps but in our approach it is nearly 1.3 kbps.

COMPARISION GRAPH

Scenarios	Proposed (Deepender Dhull)Work	Existing Work
Data Rate	6Kbps	8Kbps
Packet Delay	0.048m/s	0.02m/s
Packet Received	70Kbps	81Kbps
Packet Loss	2Kbps	1.3Kbps

Tabel 2: Comparision Between Existing Work and Proposed (Deepender Dhull) Work

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

In this research work, we have proposed an intelligent mechanism that helps to overcome the congestion problem arises during packet transfer in wireless sensor network, our technique provides the solution to the mobile sensor nodes under various circumstance and the obtained results were improved comparing to the techniques already proposed. As number of other techniques are used in swarm intelligence and metaheuristics, the given optimization problem can also be solved using genetic algorithm, honeybee algorithm, simulated annealing and others. Metaheuristics are generally and efficiently used for combinatorial optimization in which an optimal solution is sought over a discrete search-space. Another case problem is the travelling salesman problem where the search-space of candidate solutions grows faster than exponentially as the size of the problem increases, which makes an exhaustive search for the optimal solution infeasible. Compared to other traditional heuristics, metaheuristics are more abstract procedures that make use of the low-level heuristics or search algorithms; thus, metaheuristics use concrete heuristics or algorithms

.

6.2 Future Scope:

As the future scope of work, the same paradigm and problem can be solved using genetic algorithm or simulated annealing which are prominent metaheuristic techniques

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