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# HYBRID PARTICLE SWARMS FOR ENERGY-EFFICIENT ROUTING IN HETEROGENEOUS WIRELESS SENSOR NETWORKS

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**Abstract-** Many solutions have been proposed where energy awareness is essential consideration for stable routing. In this proposed work, hybrid of reactive flock-cluster and proactive-cluster routing algorithm based on the residual energy, fitness function and Euclidean distance of nodes in heterogeneous wireless sensor network. The algorithm consists of both reactive and proactive setup phase. In a reactive way, multiple paths are built between the source and destination of a data session. During the course of the session, paths are continuously monitored and improved in a proactive way and update the information at continuous time events by using fitness function of each node. By simulation experiments, it is shown that the performance of the proposed work outperforms the standard AODV routing algorithm.

**Keyword:** heterogeneous wireless sensor networks, particle swam optimizer, flock-cluster, proactive cluster

## I.INTRODUCTION

Clustering means the act of partitioning an unlabeled dataset into groups of similar objects. Each group, called a `cluster', consists of objects that are similar between themselves and dissimilar to objects of other groups. In the past few decades, cluster analysis has played a central role in a variety of fields ranging from engineering computer sciences life and medical sciences to earth sciences and social sciences. In architecture backbone nodes use directional communications (higher tier), either Free Space Optical (FSO) or directional Radio Frequency (RF), to aggregate and transport traffic from hosts at lower layers (lower tier).The advantages of directional wireless communications can be well exploited at the upper layer, where line of sight constraints are less restrictive and interference-free and point-to-point communication links can provide extremely high data rates.

The focus research reported here is the development of a novel machine learning algorithm based on the Particle Swarm Optimization (PSO) Concept to address the problem of routing in wireless sensor networks. Rather than maintain a single particle swarm that encompasses the entire sensor network, our approach is based on overlapping swarms that localize information dissemination. The use of the PSO approach in this environment provides two interesting advantages. The first is the ability to make path determinations through the network graph based on a variety of parameters (e.g., power, hop count). This flexibility allows the network to determine the least resource intensive path at any point in time. The second benefit is the ability to localize the distribution of these parameters between nodes. Localization reduces control traffic flooding throughout the networks thus reducing energy consumption while still allowing nodes to make valid route selection decisions. This paper presents the Particle-based Routing with hybrid Swarms for Energy Efficiency algorithm as a potential solution to conserving energy in sensor networks.

 

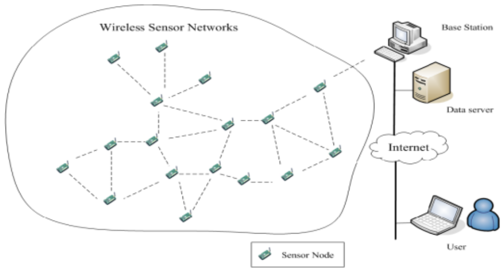


*Figure 1.1 Hierarchical Wireless Sensor Network Architecture*

Sensor networks can improve our lives in many ways. Wireless sensor networks (WSNs) are applied across a broad range of application domains. A sensor network is an infrastructure that consists of sensing, computing and communication elements. An example of a wireless sensor network is shown in Figure 1.1. The network gives an administrator the ability to instrument, observe and react to events in a specified environment. The main object of wireless sensor networks is to reliably detect and estimate event features from the collective information provided by sensor nodes.

A heterogeneous wireless sensor network is one where the constituent motes are not all of the same hardware design, and may not execute the same code, or perform the same functions. In particular, various sensors may not have the same maximum battery capacity. Energy saving always is a key concern in sensor networks. Because some of environments might be very dangerous, for instance, forest and building fire, volcanic mountain and under-water. Nobody would like to recharge or change batteries of sensor nodes in the network.

## II.LITERATURE SURVEY

Self-Organizing Broadband Hybrid Wireless Networks describes hybrid communication mode that enables them to communicate with both the terminal wireless nodes and the other base station nodes. Base station nodes form a backbone for the network, through the use of point-to-point communication technologies such as free space optical (FSO) and directional radio frequency (RF) communications [1].Optimizing Performance of Hybrid FSO/RF Networks in Realistic Dynamic Scenarios presented by how optimization performance of FSO/RF networks under various dynamic scenarios. A Mobility-Based Clustering Approach to Support Mobility Management and Multicast Routing in Mobile Ad-Hoc Wireless Networks presented how mobility supported in a mobile ad-hoc wireless network and routing capability [2].A Spatial Clustering Algorithm Using Swarm Intelligence explains how clustering under swarm intelligence based on the spatial method using RPGM model.

The optimization of network parameters for a WSN routing process to provide maximum network lifetime might be considered as a combinatorial optimization problem. Many researchers have recently studied the collective behavior of biological species such as ants as an analogy providing a natural model for combinatorial optimization problems developed routing using ant colony optimization (ACO). Ant colony optimization (ACO) algorithms simulating the behavior of ant colony have been successfully applied in many optimization problems such as the asymmetric traveling salesman, vehicle routing, and WSN routing [3].Clustering Analysis explains how document clustering done in flocking based algorithm under A Flocking Based Algorithm for Document data mining application [3].A New Approach of Data Clustering Using a Flock of Agents presented by how data clustering approach used in flocking agent. Stability Analysis of Swarms explains about the stability analysis under dynamic scenarios under swarm intelligence [4].

Effective Leadership and Decision Making in Animal Groups on the Move explains leadership and decision making based upon the local interactions in animal groups in nature. Small-World Network-Based Coordinate Predictive Control of Flocks" presented how network based predictive control and optimization in the flocks [5].Particle Swarm Optimization Method for Image Clustering explains PSO method in the image processing using image clustering method under global optimized value. Reconfiguration and Control in Directional Mobile Ad-Hoc Networks explains about the network reconfiguration and network release provides predictive control in DWNs in mobile ad-hoc network [6].

## III.HETEROGENEOUS MODEL FOR WSN

Most of the protocols designed for WSNs assume that the sensors have the same capabilities in terms of storage, processing, sensing, and communication. The resulting network is said to be homogeneous. In these types of networks, a pair of sensors would have the same lifetime if they have the same energy consumption rate. Some sensing applications, however, use sensors with different capabilities and accordingly the resulting network is said to be heterogeneous. In the real world, the assumption of homogeneous sensors may not be practical because sensing applications may require heterogeneous sensors in terms of their sensing and communication capabilities in order to enhance network reliability and extend network lifetime also, even if the sensors are equipped with identical hardware, they may not always have the same communication and sensing models. In fact, at the manufacturing stage, there is no guarantee that two sensors using the same platform have exactly the same physical properties. This taxonomy focuses on heterogeneity at the designing stage, when sensors are designed to have non identical capabilities to meet the specific needs of sensing applications.

In this section, we will present a paradigm of heterogeneous wireless sensor network and discuss the impact of heterogeneous resources. There are three common types of resource heterogeneity in sensor node computation -al heterogeneity, link heterogeneity, and Energy Heterogeneity

a) **Computational heterogeneity** means that the heterogeneous node has a more powerful microprocessor and more memory than the normal node.

b) **Link heterogeneity** means that the heterogeneous node has high-bandwidth and long-distance network transceiver than the normal node. Link heterogeneity can provide more reliable data transmission.

c) **Energy heterogeneity** means that the heterogeneous node is line powered, or its battery is replaceable. Among above three types of resource heterogeneity, the most important heterogeneity is the energy heterogeneity because both computational heterogeneity and link heterogeneity will consume more energy resource.

## IV.PROPOSED WORK

### 4.1 PARTICLE SWARM OPTIMIZATION

The particle swarm optimization algorithm, originally introduced in terms of social and cognitive behavior [1], solves problems in many fields, especially engineering and computer science. The individuals, called particles henceforth, are flown through the multidimensional search space with each particle representing a possible solution to the multi-dimensional optimization problem. Each solution's fitness is based on a performance function related to the optimization problem being solved.

The movement of the particles is influenced by two factors using information from iteration-to-iteration as well as particle-to-particle. As a result of iteration-to- iteration information, the particle stores in its memory the best solution visited so far, called p-best, and experiences an attraction towards this solution as it traverses through the solution search space. As a result of the particle-to particle interaction, the particle stores in its memory the best solution visited by any particle, and experiences an attraction towards this solution, called g-best, as well. The first and second factors are called cognitive and social components, respectively .After iteration, the p-best and g-best are updated for each particle if a better or more dominating solution (in terms of fitness) is found. This process continues, iteratively, until either the desired result is converged upon, or it is determined that an acceptable solution cannot be found within computational limits. For an n dimensional search space, the $i^{th}$ particle of the swarm is represented by an n-dimensional vector, $X_i = (x_{i1}, x_{i2} \ldots\ldots x_{in})$. The velocity of this particle is represented by another n dimensional vector $V_i=(v_{i1}; v_{i2}\ldots\ldots v_{in})$. The previously best visited position of the ith particle is denoted as $P_i=(p_{i1}, p_{i2}, \ldots\ldots\ldots p_{in})$. `g′ is the index of the best particle in the swarm. The velocity of the $i^{th}$ particle is updated using the velocity and position update equations given by

$$v_{id} = v_{id} + c_1 r_1 (p_{ld} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{4.1}$$

$$x_{id} = x_{id} + v_{id} \tag{4.2}$$

where d = 1, 2....n ; i = 1; 2....S , where *S* is the size of the swarm; c1 and c2 are constants, called cognitive and social scaling parameters respectively (usually, c1 = c2 ; r1 , r2 are random numbers, uniformly distributed in [0, 1]). Equations (2.1) and (2.2) are the initial version of PSO algorithm. A constant $V_{max}$, is used to arbitrarily limit the velocities of the particles and improve the resolution of the search. Further, the concept of an inertia weight was developed to better control exploration and exploitation. The motivation was to be able to eliminate the need for $V_{max}$. The inclusion of an inertia weight (*w)* in the particle swarm optimization algorithm was first reported in the literature). The resulting velocity update equation becomes:

$$v_{id} = w.\, v_{id} + c_1 r_1 (p_{ld} - x_{id}) + c_2 r_2 (p_{gd} - x_{id}) \tag{4.3}$$

The optimal strategy is to initially set *w* to 0.9 and reduce it linearly to 0.4, allowing initial exploration followed by acceleration toward an improved global optimum.

## 4.2 ROUTING ALGORITHM USING PSO

Particle swarm optimization is mainly a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to given measure of quality. For solving any optimization problem we have to first formulate the problem according to optimization problem. In this proposed algorithm we have to choose the best path according to fitness value which is according to the minimum distance to be travelled by a data up to base node, since we are dealing with energy efficient routing, more the distance more the energy will be lost in sending data. So to calculate fitness value we are using PSO and generating an optimum path taking consideration in all sensor nodes.

### 4.2.2 FITNESS FUNCTION

To find optimize path using PSO, need to find the fitness value of each path .This fitness value will be used to select the local best and global best for PSO. The path having minimum fitness value will be the best optimal solution.

Fitness value = dist(i,j) + dist(j,base) (4.4)

where i , j are the node distance.

### 4.2.3 HYBRID PARTICLE SWARM OPTIMIZATION BASED ROUTING

This routing algorithm is hybrid of reactive flock-cluster and proactive-cluster routing algorithm which was illustrated into two phase

Phase 1: [Initialization Phase]
for (s = 0 to number of solutions or populations).
{
for (d = 0 to number of sensor nodes).
{
Randomly solutions are selected.
Compute new route using solution.
End for.
}
Compute fitness value of initialized solution.
{
Compute global best and local best.

End for.
}
Phase 2: [Update Phase]
While criteria does not match
{
for (s = 1 to number of solutions)
{
for (d = 1 to number of sensor nodes).
}
Update solution using PSO update equation.
Generate new path based on update solution.
End for.
}
Compute fitness value for updated route.
Compute global best and local best.

To find best optimal path with least energy usage we have used Particle Swarm Optimization (PSO).We set an initial solution by selecting a random number of solutions from the set of x! Solution x is the total number of solutions. After getting initial random solutions we calculate fitness value of each solution, according to equation (4.1).After that we calculate best among the entire solution and set it as initial global and local best.PSO update equation is used to update old solution and generate new solutions and their nodes are calculated. These solutions along with their nodes are then used to find the fitness value of each solution. The process will be repeated till the given iteration is satisfied. Based on this continuous iteration and fitness value the solution which is better is replaced than its other solutions.

### 4.3 PERFORMANCE ANALYSIS

There are different mobility models which are used for simulating the ad hoc networks in different environments. The most commonly used are

a) Random waypoint mobility model
b) Reference point group mobility model
c) Freeway
d) MANHATTEN mobility model

In this work, group mobility is considered. In group mobility model a mobile node begins the simulation by waiting a specified pause time. After this time it selects a random destination in the area and a random speed distributed uniformly between some range. After reaching its destination point, the mobile node waits again pause time seconds before choosing a new way point and speed. Traffic sources are CBR (continuous bit rate). The source destination pairs are spread randomly over the network.

By changing the total number of traffic sources, we get scenarios with different traffic loads. For small traffic loads (10, 20, 30 sources), the packet rate at the source node is 4 packets/sec 40 sources, a smaller rate of 3 packets/sec for 50 nodes. Only 512-byte data packets are used. Field- configurations is used as 1000m × 1000m with 50 nodes. Each node starts its journey from a random location to a random destination, with a randomly chosen speed uniformly distributed between 0 and 20 m/sec.

| **Parameters** | **Values** |
|---|---|
| Terrain size | 1000m×1000m |
| Start simulation time | 1msec |
| Total no. of nodes | 50 |

 

| | |
|---|---|
| Initial Energy | 2.3 mJ/node |
| All weighting parameters | $w_p=w_l=w_a=1$ |
| Step size (ρ) | 0.01 |
| Residual energy | 0.2 mJ/node |
| Total simulation time | 50msec |

*Table 1.1 Simulation Parameters*

Several variations of AODV have been proposed which incorporate energy conservation into the route selection mechanism without energy awareness wireless networks will provide high packet delivery ratio, minimum over head and less throughput for network stability. But it provides limited support for subnet route and does not keep the information up-to-date.

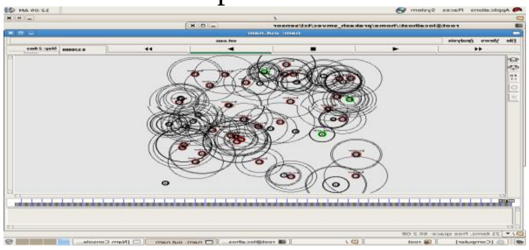

*Figure 4.1 Simulation using Flock-Clustering Mechanism*

Flocking optimization framework can be executed in distributed manner based on discrete time events. Because each node only uses local information from neighbor nodes and the terminal nodes in its coverage range which organize the group dynamically.

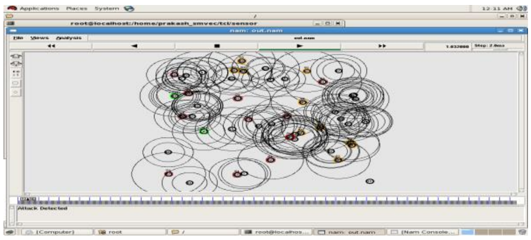

*Figure 4.2 Simulation using Hybrid PSO-AODV Mechanism*

For the following simulation runs, the variables C1 and C2 are set to 1.0 and 0.01, respectively. The selection of these values for C1 and C2 was driven by a numerical analysis of possible values providing sufficient weight to both the hop count and consumed energy levels while still resulting in distinct fitness values. The hypothesis is that we will see statistically significant improvement in the difference between average residual energy with the sensor network operating with the hybrid PSO-AODV algorithm.

Using NS-2 as simulation environment, the simulation parameters used to evaluate the performance parameters are given below:

**4.3.1 Performance Metrics**

a) **Throughput (bytes/sec):** This is the ratio of the data packets delivered to the destination to those generated by the CBR sources.

b) **Packet delivery ratio:** The ratio of the number of delivered data packet to the destination. This illustrates the level of delivered data to the destination.

PDR = ∑ Number of packet receive / ∑ Number of packet send

 

c) **Overhead:** As mentioned before, the overhead caused by maintenance and protocol overhead can be reduced by employing various self-organization mechanisms. It is important to keep analyzing the globally visible overhead. In case of preventing the maintenance of global state information, it will always involve some amount of additional work to perform the desired operation. On a global point of view, there should be a reduction of necessary overhead visible if the right mechanisms for the particular applications have been chosen and they are properly configured.

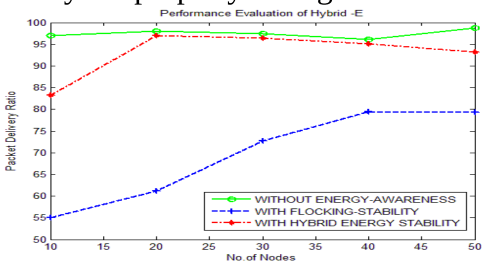


*Figure 4.3 Packet Delivery Ratio Vs No. of Sensor Nodes*

From the above performance the packet deliver ratio of proposed work is nearer to the existing AODV protocol without energy constraints have good self organization mechanism. Flocking optimization framework can be executed in distributed manner based on discrete time events provide less packet delivery ratio when compared to hybrid mechanism. Because each node only uses local information from neighbor nodes and the terminal nodes in its coverage range which organize the group dynamically.

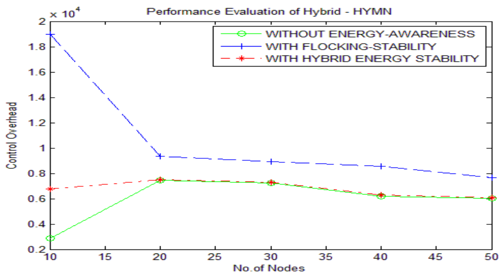


*Figure 4.4 Control Overhead Vs No. of Sensor Nodes*

While the energy levels were significantly different, the packet delivery ratio (number of packets transmitted by the sources / number of packets received by the sink) for both protocols was over 94%. This first simulation run shows promising initial results, but does not demonstrate behavior of the protocols once nodes begin depleting their batteries. To observe the protocols behaviors under these conditions, the second set of simulation runs increased the simulation run time

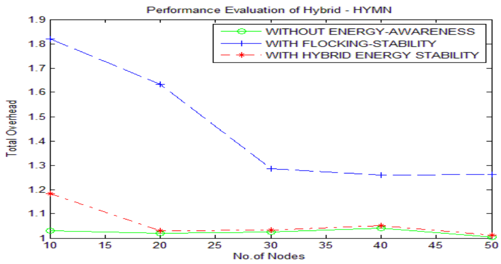


*Figure 4.5 Total Overhead Vs No. of Sensor Nodes*

From Fig and Fig PSO-AODV on the other hand, dynamically changes routes throughout the length of the simulation run based on the fitness function calculation, spreading the depletion of energy across a more diverse set of nodes. Control overhead because of the exchange of routing updates. Overhead traffic peaks at 15 km/h, where it takes the control overhead of AODV in various mobility models less control overhead which is nearer to proposed energy efficient cluster based routing protocol which lead to reduce overall overhead of network.

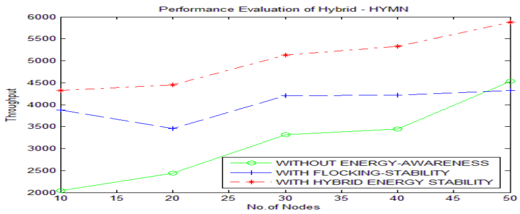


*Figure 4.6 Throughput Vs No. of Sensor Nodes*

PSO-AODV has very good performance. Proposed framework mechanism keeps the network information up-to-date to stabilize the network by using hierarchal control architecture based on energy constraint and PDR. And improves the performance in various dynamic scenarios by reducing nodal as well as link information between arbitrary pairs of nodes across the entire network by gathering overall network information provide stable routing provide maximum throughput because of low overhead due to global optimum routing when compared to existing Flocking mechanism.

## V.CONCLUSION

Energy awareness of wireless sensor networks will provide high packet delivery ratio, minimum over head and low throughput under cluster stability. But it provides limited support for subnet route and keeps the information up-to-date at discrete set of time events. The proposed framework mechanism keeps the information up-to-date periodically to stabilize the cluster by using hierarchal control architecture based on residual energy and packet delivery ratio. This mechanism improves the performance in various dynamic scenarios under constant bit rate traffic by reducing nodal as well as link information with increase of node density.

## VI. FUTURE ENHANCEMENT

In future, the stability analysis of HWSNs in a complex dynamic environment is still an open problem, and plans to conduct a theoretical analysis of the stability of HWSNs under by using other hybrid combination of algorithm for better performance at different distance threshold and resolution in the context of self organization and control.

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