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Energy Efficient Task Allocation Using Mutant Particle Swarm Optimization in WSN

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ABSTRACT - *Energy consumption is currently a key issue in research for future sensor networks. This paper presents a novel approach to sensor network routing based on energy consumption. The unique routing algorithm uses swarm intelligence, which is computationallyefficient.*
KEYWORDS: *Communication, Sensor Networks, Routing, Swarm Intelligence, Ant System.*

I. INTRODUCTION

Communication routing in a network is a NP hard prob- lem[1] and evolutionary algorithms play an important role in solving routing problems. In this paper, a building sensor network consisting of wired and wireless nodes possessing energy constraints[2] between nodes is considered. Each node in the network has the ability to communicate with any of its peers. The objective is transferring messages with min- imum energy using evolutionary swarm algorithm.

II. BUILDING SENSORNETWORK

In Figure 1, a graphical representation of an example building sensor network is shown. Where a two building net- work with four floors and rooms equipped with or without sensors (denoted by shaded circles, and the arrows denotes the route taken by the agents) is shown. The number of sen- sors is independent of the floor(s) and room(s). Swarm agents set up a communication route incorporating all nodes. The nodes are not homogenous in terms of energy.

During communication the sensor nodes on each floor form clusters in a decentralized manner with no cluster heads and communicate with its peers regardless of the type of their links i.e., wired or wireless (energy loss isdependent

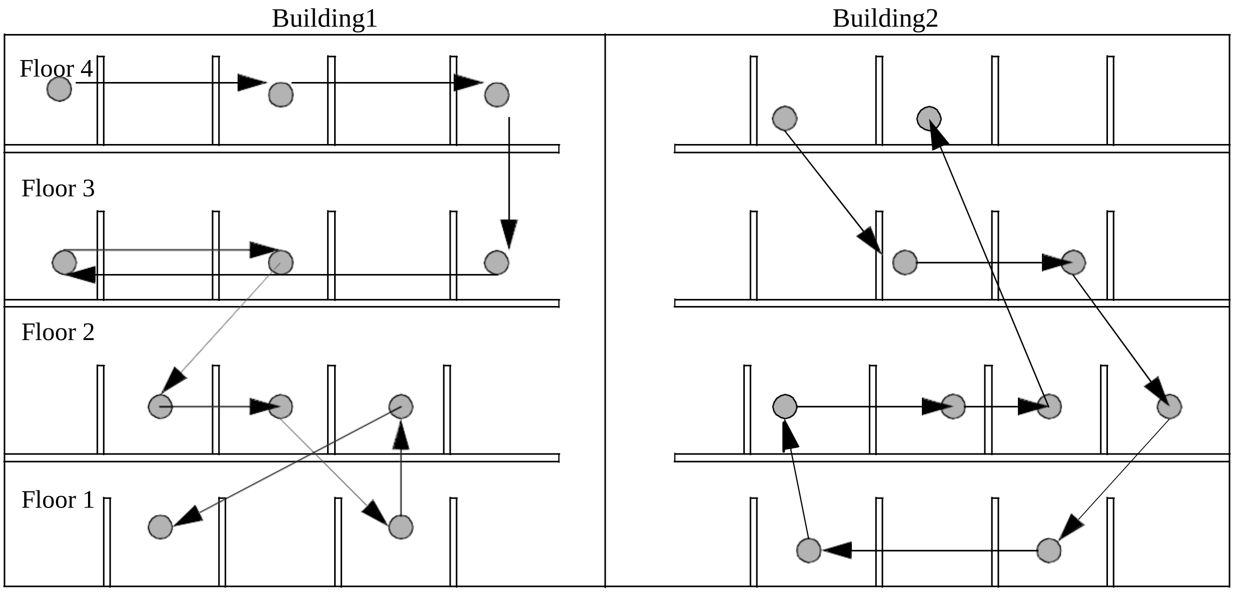

Fig. 1. Communication Routing in a Building Sensor Network Using Swarm Agents

onlink type). Using an evolutionary algorithm known as swarm intelligence [3], we optimize the resources achieving optimality and reachability [4]. The swarm algorithm for solving communication routing problem is discussed in the next section. Simulation results provide insight into compu- tational efficiency in the fourth section. The fifth section concludes with a discussion on future progress of thepaper.

III. SWARM AGENTS & BUILDINGNETWORK

Swarm intelligence[3] is the collective behavior from a group of social insects, namely ant, birds, etc., where the agents (ants) communicate in the system eitherdirectlyor indirectly using a distributed problem solving approach. This approach supports an optimized routing design, avoids stag- nation, and prevents centralization of the network nodes. Routing in wireless network is never static; hence this intelli- gent sensor approach provides a solution to dynamic and dis- tributed optimization problems. Thus making the network robust, flexible, decentralized, coherent and self organized.

Swarm agents (ant agents) [5], [6], [7] are randomly

e Level, Transition Probability and the Tabu-Lists. Real life ants deposit a chemical substance called phero- mone, which serves as a trail for the other ants to follow. The ant system mimics this pheromone deposition by laying pheromones depending on both energy level atthe sensor node and the distance from one node to another (Pheromone Level).

The agents travel through the nodes followingphero- mones and dissipating energy. The pheromone is updated upon completing a tour by every agentby

$$\psi_{ij}(t)=\rho(\psi_{ij}(t-1))+\frac{Q}{D_t E_t} \tag{1}$$

where $\psi_{ij}$is the pheromone deposition with i as the source, j as the destination, ρ and Q arbitrary constants, D_t the total distance of the current tour and $E_t$the energy dissi- pationat that node. The transition probability for wired net- work is computedas

$$P_{ij}=\frac{(\psi_{ij})^{\alpha}\cdot\left(\frac{1}{D_{ij}}\right)^{\beta}\cdot(E_{ij})^{\alpha}}{\sum(\psi_{ik})^{\alpha}\cdot\left(\frac{1}{D_{ik}}\right)^{\beta}\cdot(E_{ik})^{\alpha}} \tag{2}$$

Where, $D_{ij}$is the euclidean distance, $E_{ij}$is the energy level at that node and α, and β are arbitrary constants. The transition probability gives the movement of ant with respect tothe pheromone deposition and the energy level of the node at that time. Using these two conditions the node with energy level less than the threshold is avoided thereby reducing the pheromone deposition at that node rendering that route the least taken in the network. This scheme of routing providesa robust network as the failed nodes are avoided by the agents thereby avoiding a total failure of the network.

The third feature of the AS is tabu-list which serves as a visit log that maintains information about each visit to a node, the distance taken and the energy level at that node. With these updates of the environment, the ant agent takes an efficient route which makes them robust and computa- tionallysimpler.

The energy level is calculated by means of the euclideandistance D_{ij}. The estimation of energy dissipation includes a link budget constant k and distanceD_{ij},

$$D_{ij}=\sqrt{(X_i-X)_j^2+(Y_i-Y)_j^2} \tag{3}$$

For a wired link the energy dissipation is estimated as

$$\Delta E=k\cdot D_{ij} \tag{4}$$

and for a wireless link, the change in energy is

$$\Delta E=k\cdot D_{ij} \tag{5}$$

The energy dissipation for a tour is calculated as the energy at that node with respect to the energy dissipated an agent during a tour in datatransfer.

$$E_i(t)=E_i(t-1)-\sum_j \Delta E_{ij} \tag{6}$$

IV. SIMULATION RESULTS

The building sensor network considered here has two

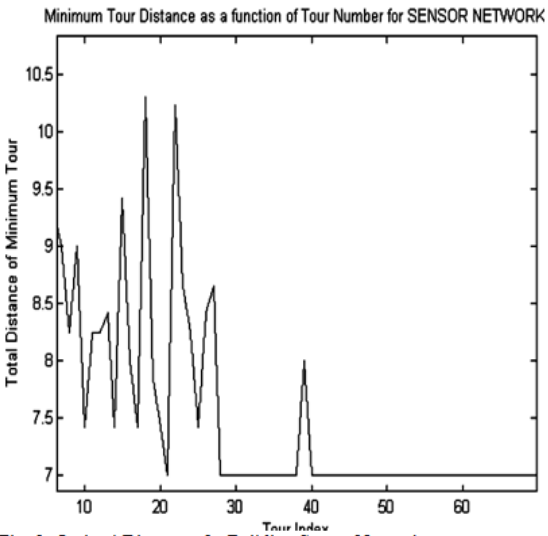

Fig. 2. Optimal Distance of a Building Sensor Network

floors with 5 and 3 sensors on each floor, respectively. These are placed using two-dimensional cartesian co-ordinates. The sensor's energy at each node is initialized to the distance between the nodes with a factor of 100, the pheromone level isinitializedtoa constant(10)and the thresholdatallnodes is set to 50. Figure 1 shows the network under zero node fail- ure.
In Figure 2 optimal distance is achieved by the agent by sharing their knowledge of the system with their neighbors using the tabu-list. The mean and standard deviation of this problem is 8.5467 and 0.4288respectively.

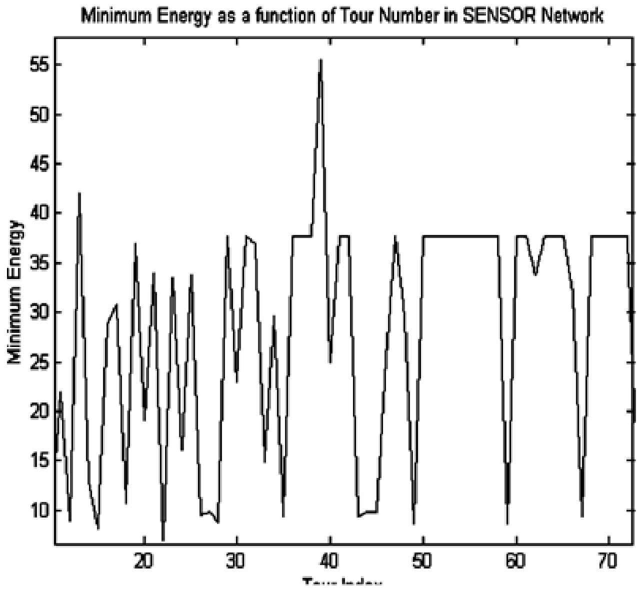

Fig. 3. Optimal Energy of the Building Sensor Network in a Tour

In Figure 3, the minimal energy dissipation of a sensor network is shown. Where the energy dissipation is reduced gradually over a period of time.

Figure 4 gives the average energy level of the sensor net- work which gives a detail insight of the energy level avail- able in the network and the ability of nodes to communicate.

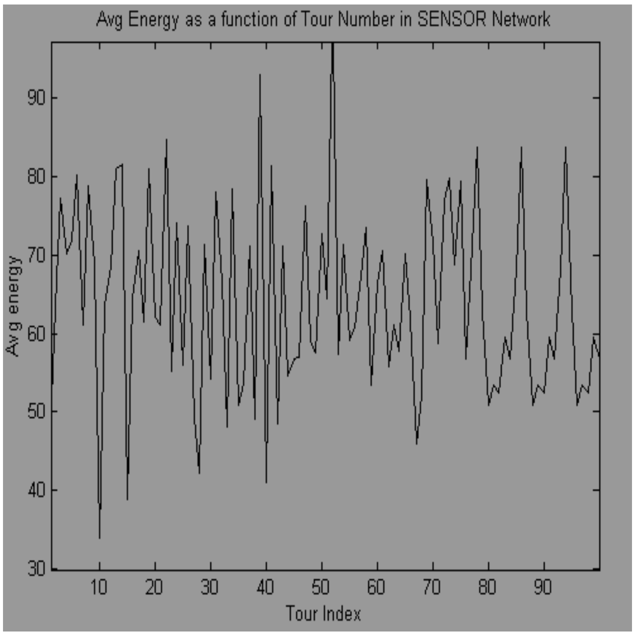

Fig. 4. Average Energy of the Building Sensor Network in a Tour

The route taken by the last ant agent is shown in Figure 5, when compared with the agents previous

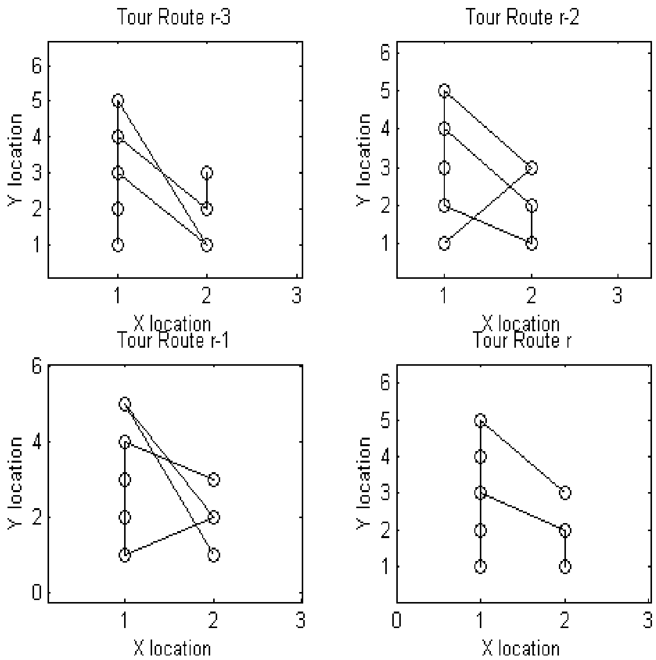

Fig. 5. Routing in Building Sensor Network - The last agent's route 8 Sensors

routes r-3 and the last route r, the efficient route is picked by the agent. Thus obtaining an optimal solution.

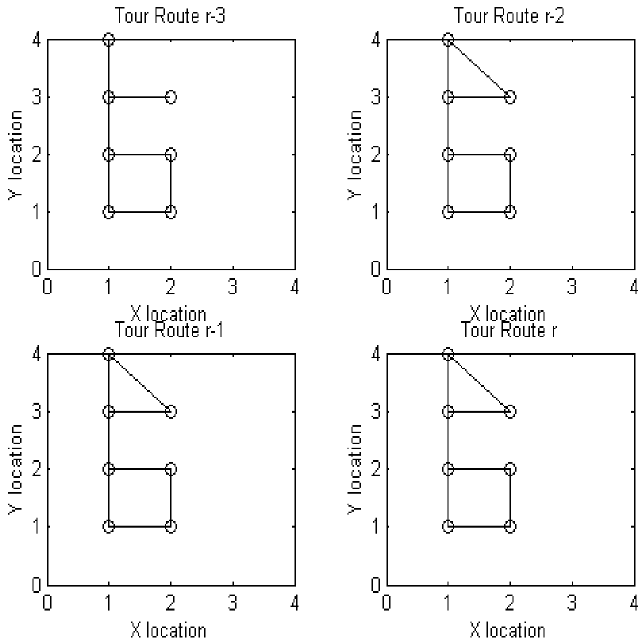

Fig. 6. Identical Routes of the agent -Routing in Building Network with 7 Sensors

hen identical routes are taken by three agents we define convergence as shown in Figure 6.
The results are summarized in Table I , where for a given problem set the mean and the standard deviation of the dis- tance and energy is listed. As the number of tours increases the global solution with minimum distance and energy is achieved.

TABLE I. PERFORMANCE VS. NO OF RUNS USING AGENTS

No Of Runs	Mean of Distance	Mean of Energy	SD of Distance	SD of Energy
5	11.8980	0.9483	1.6566	0.1705
15	13.0534	0.9418	1.9542	0.1643
30	10.7995	0.9170	2.0674	0.1575
55	8.6058	0.8968	1.9492	0.1334
105	8.3467	0.8328	1.2504	0.1310
180	8.1124	0.8152	0.5722	0.1222
280	7.9271	0.7218	0.4540	0.0908
1280	7.6180	0.7074	0.6607	0.0727

III. CONCLUSION AND FUTUREWORK

The evolutionary algorithm used under the above circum- stance reaches optimality with respect to routing, energy dissipation and robustness.

In the future the link layer will be merged with thenet- work layer to perform optimization and energy conservation simultaneously. Further, the swarm agents will be incorpo- rated with a life factor to determine effectiveness of the algorithm versus the survivability of the agents in thenetwork.

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