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# Balancing The Performance of a Sensor Network Using an Ant System

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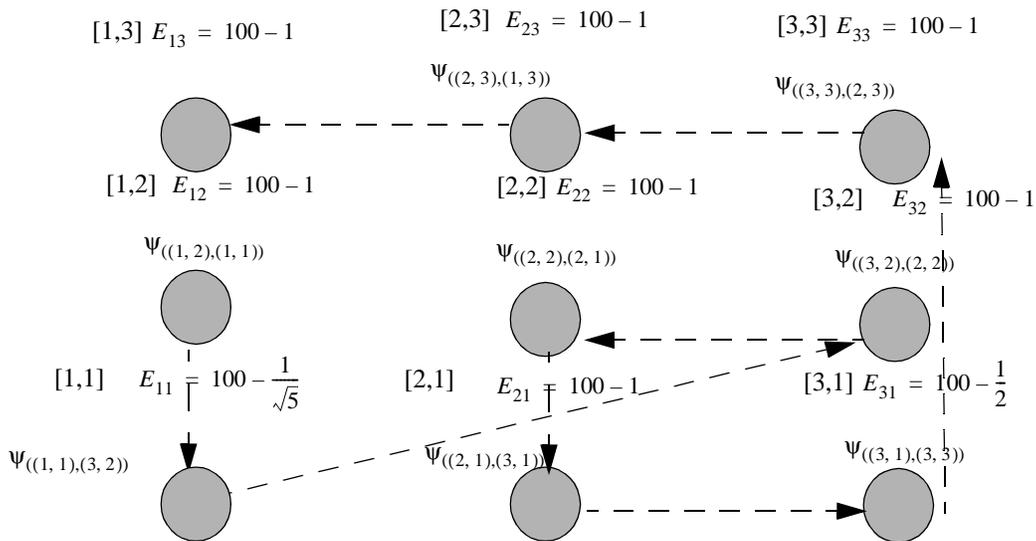
**Abstract** - In a sensor network consisting of both wired and wireless links, the nodes sense, collect and distribute dynamic information from one sensor to the other. Energy consumption is a key issue in the sensor's communications since many use battery power, which is limited. The sensors also have limited memory and functionality to support communications. Therefore, there is a need to balance energy usage with obtaining the shortest communication distance. This paper presents a novel approach to selecting message routes using an ant system. Parameters controlling the convergence of the ant system are analyzed in terms of wired and wireless networks.

Time delay is addressed first by assuring that each node is visited once and then by minimizing the communication distance. The sensor nodes have limited energy to communicate, sense, and process data. The ant system manages the energy used in the communication process which increases the life of the sensor node.

Two factors, optimality and reachability, are used to assess the effectiveness of this evolutionary algorithm. Optimality is the ability to find optima within a time constraint. This may be a local optimum rather than the desired global optimum. The total communication distance is analyzed to determine when an optimum is found. The ant system will not fluctuate in its solution after finding an optimum. Reachability is the process of obtaining the global optimum solution. The solution is then studied to verify that it is the global solution.

## I. INTRODUCTION

This paper presents an ant system is presented that is able to optimize energy usage and communication time for a wired/wireless sensor network. Energy and time delay are two critical performance parameters in sensor networks.



$$T = \{ (1,2), (1,1), (3,2), (2,2), (2,1), (3,1), (3,3), (2,3), (1,3) \}$$

Figure 1. Sensor Network Using Ant System

This paper presents an approach that can be easily extended to cover other performance factors such as sensor failure, irregular sensor spacing, and different sensor processing and reporting needs. The mobile agents in this ant system are designed to inherently overcome these issues through their interaction with the nodes in terms of energy and their ability to change pheromone levels. The pheromone levels are only changed after the ants compare their solutions with the other ant's solutions. These two mechanisms support a robust network in a decentralized manner for either wired or wireless systems.

Parameter selection in terms of optimality and reachability is the focus of this paper for both wired and wireless sensor networks. In the second section, the ant system is described in detail. The selection of an ant system approach is justified and the details concerning this system's design are given. Simulation results provide insight into parameter selection. are given in the third section. The paper concludes with the fourth section discussing conclusions and future work.

## II. ANT SYSTEM

Swarm intelligence[1] is the collective behavior from a group of social insects, namely ants, where the agents [ants] in the system communicate interactively either directly or indirectly in a distributed problem-solving manner. The ants work together within the network to achieve an optimal solution. The ants move towards the optimal solution by sharing their own knowledge with their neighbors. The initial set of ants traverse through all the nodes in a random manner, and they leave trails by depositing pheromones. The pheromones on the paths work as a means of communication between the other ants. The ants use the pheromones to help select the best route through the network. The most popular paths have the greatest pheromone level.

The ants are energy aware and know the energy status of each sensor node. As the ant moves from node to node, energy is lost through this communication. The ant stops using a node once its energy is depleted. New paths are set up that avoid the node so that communication continues without the degraded sensor.

A Tabu-list serves as memory tool listing the set of nodes that a single ant agent has visited. The ant's goal is to visit every node in the network once but only once. Once all the nodes have been visited, the ant has completed a tour. The pheromones on all the paths are updated at the end of a tour. The pheromone deposition, tabu-list, and energy monitoring help this novel ant system (AS) to obtain a optimal solution and adapt it as nodes degrade.

### A. GRAPHICAL ILLUSTRATION OF THE ANT SYSTEM

Three key elements in this AS include the pheromone deposition, energy tracking, and tabu list maintenance. A single

tour illustrating these elements is given in Figure 1. This suboptimal tour is represented by circles for the nodes and dotted arrows for the paths. The node's location is the 2 dimensional cartesian coordinates for this simulation. All of the nodes begin with an assigned initial energy level of 100 as illustrated. The figure also illustrates the loss of energy that is the reciprocal of the distance travelled by the agent to reach the next node. This Euclidean distance is based on the cartesian coordinates. The tour begins at any node in the figure and ends when all the nodes are visited. The Tabu list contains a record of the path taken by each agent and is found at the bottom of Figure 1. The pheromones are updated and the list is cleared after each tour is completed. The change in pheromones is a function of the amount of pheromone currently on the path, and the total distance travelled by the agent. The next section described in detail the updating of the pheromones and management of the sensor node's energy level.

### B. DETAILED APPROACH

The performance of the AS is determined by the node spacing and 4 parameters:  $Q$  is an arbitrary parameter,  $\rho$ , controls trail memory,  $\alpha$  is the power applied to the pheromones in probability function, and  $\beta$  is used as the power of the distance in probability function. These AS parameters control the performance of the ant system on a specified set of nodes. Another key factor is the Euclidean distance or

$$D_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2} \quad (1)$$

where  $i$  is the source node,  $j$  is the destination node, and  $(X_i, Y_i)$  are the cartesian coordinates of the node.

The ant agents accumulate pheromones and dissipate energy as they traverse through the nodes based on the path probabilities. The pheromone is initialized and is assigned a value of 10. It is updated following each complete tour by, (AS - see [2][3][4]),

$$\Psi_{ij}(t) = \rho \Psi_{ij}(t-1) + \frac{Q}{D_t} \quad (2)$$

where  $D_t$  is the total distance travelled by ant agents during the current tour,  $i$  is the index for the source node with coordinates  $(x_i, y_i)$ , and  $j$  is the index for the destination node with coordinates  $(x_j, y_j)$ . The transition probability between nodes for a wired network is computed from

$$P_{ij} = \frac{(\Psi_{ij})^\alpha \cdot \left(\frac{1}{D_{ij}}\right)^\beta}{\sum_k (\Psi_{ik})^\alpha \cdot \left(\frac{1}{D_{ik}}\right)^\beta} \quad (3)$$

The transition probability between nodes for a wireless network is computed from

$$P_{ij} = \frac{(\Psi_{ij})^\alpha \cdot \left(\frac{1}{D_{ij}}\right)^{2\beta}}{\sum_k \left( (\Psi_{ik})^\alpha \cdot \left(\frac{1}{D_{ik}}\right)^{2\beta} \right)} \quad (4)$$

The energy is dissipated from the sensor node after each ant passes through that node. Thus, the number of ants is important as well as the sensor's efficiency in communicating information. The energy is computed differently for wired and wireless sensors. For wired sensors, it is simply the inverse of the distance traversed or

$$\Delta E_{ij} = \frac{K}{D_{ij}} \quad (5)$$

where  $K$  is a constant representing the amount of energy the sensor requires to communicate the ant over a single unit distance. For a wireless sensor, the energy is

$$\Delta E_{ij} = \frac{K}{(D_{ij})^2} \quad (6)$$

The node's remaining energy is computed by

$$E_i(t) = E_i(t-1) - \sum_j \Delta E_{ij} \quad (7)$$

The energy depleted sensor nodes are removed from the sensor network and alternative routes are found. Thus the network is remains partially functional even if some individual sensors fail.

### III. SIMULATION RESULTS

A network with 16 sensor nodes is simulated in this example with 10 ant agents. The agents are randomly placed on the nodes, and the sensor node's energy is set at 100. The node is removed from the network after its energy is depleted to a level of 50. The first set of figures corresponds to an ant system with good parameter selections. The second set of figures corresponds to a badly behaving ant system. This section concludes with a table summarizing the resulting ant system behavior for a variety of parameter settings.

In the Figure 2 and Figure 3, wireless and wired sensor network performance is depicted. The tour-distance taken by the agents in a network is plotted. The tour index is adjusted by 100. Thus, a tour index of 10 corresponds to an index of 110 in the simulation. The optimum result was achieved in the wireless sensor after a 128 iterations or tours. This would correspond to 28 in the plot. Similarly, the wired sensor network achieves the optimum answer after 123 iterations. The 4 AS parameter settings are given in the figure title. The  $Q$  parameter is lower of the wireless network at 0.9 in comparison to 1 for the wired network. When the same parameter values are used, the wireless sensor network converges to a solution less efficiently than the wired network. This is related to the squaring of the distance in the AS parameter.

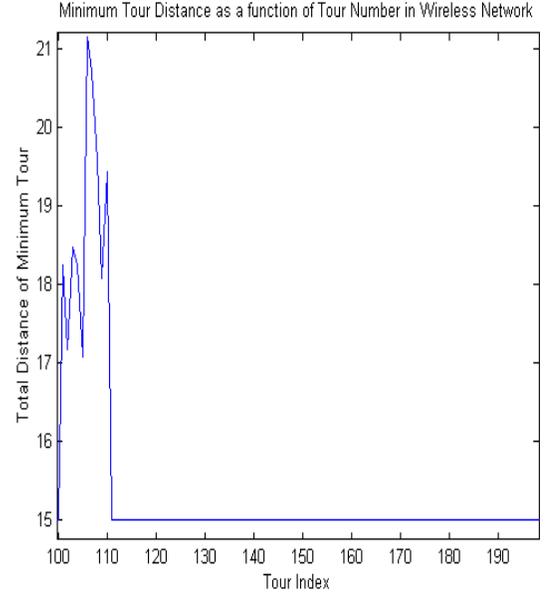


Figure 2. Reachability in Wireless Sensor Network Using Ant system- at 128 runs -  $Q: 0.9$   $Rho: 0.7$   $Alpha: 4$   $Beta: 7$

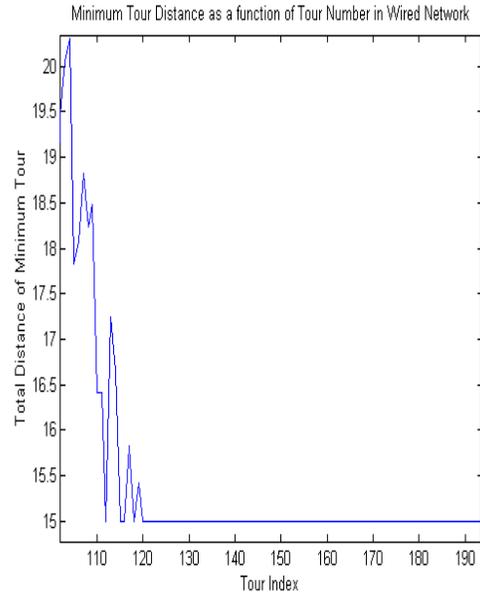


Figure 3. Reachability in Wired Sensor Network Using Ant system- at 123 runs  $Q: 1$   $Rho: 0.7$   $Alpha: 4$   $Beta: 7$

The energy dissipated from the sensor nodes is tracked for both the wireless and wired sensor network. In Figure 4 and Figure 5, the energy dissipated during the ant tour is averaged over all the sensor nodes. This plot illustrates the energy savings that occurs when the optimal solution is found. After optimality is reached, less energy is spent by all the sensor nodes during the communication process.

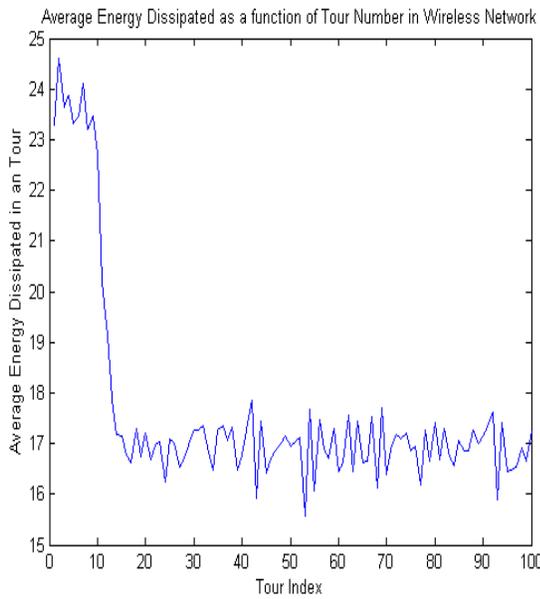


Figure 4. Energy Dissipation - Wireless Sensor Network - Best parameter condition [Q: 0.9 Rho: 0.7 Alpha: 4 Beta:7]

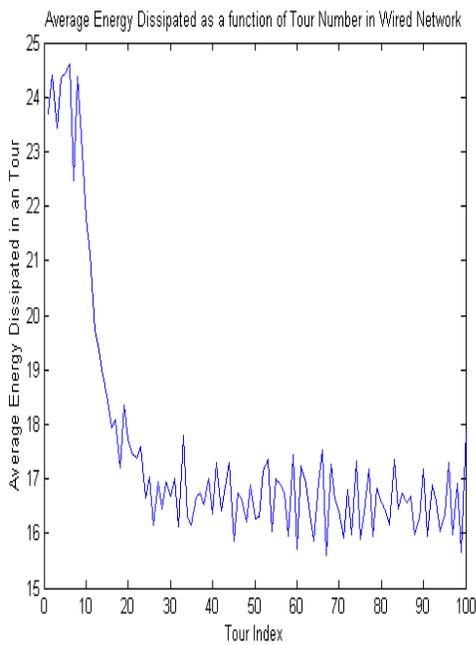


Figure 5. Energy Dissipation - Wired Sensor Network - Best parameter condition [Q: 1 Rho: 0.7 Alpha: 4 Beta:7]

A poorly functioning ant system for both wired and wireless sensor network is shown in Figure 6 and Figure 7 . The ant system achieves a local minima but exhibits a stagnation behavior. Thus, the algorithm attempts to search for a global minima while stuck at a local minima. Hence in situations

like this the ant system still works efficiently by continuing to search for a better solution.

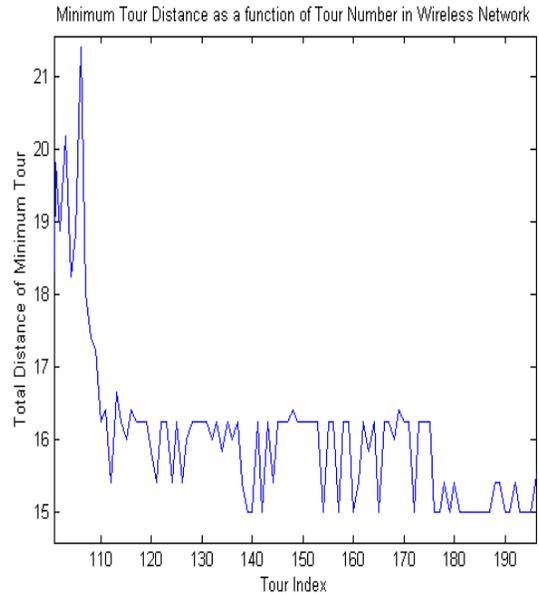


Figure 6. Worst Case - Reachability in Wireless Sensor Network Using Ant System Q= 0.9 Rho = 0.5 Alpha = 4 Beta = 5

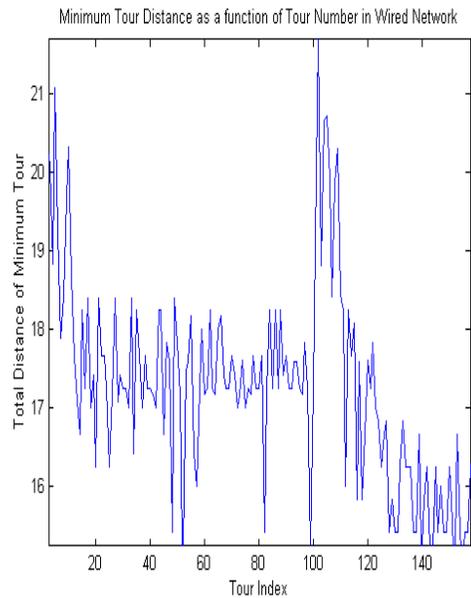


Figure 7. Worst Case - Reachability in Wired Sensor Network Using Ant system- at 123 runs Q: 0.5 Rho: 0.7 Alpha: 4 Beta:5

In the Figure 7 , the wired sensor network continues to search for a better solution but never reaches either a local or global minima. The low Q value and lower beta value significantly degrade the ant system.

Figure 8 and Figure 9 show four consecutive tours taken by an ant agents. Since the tours vary significantly, it

#### IV. CONCLUSION AND FUTURE WORK

The performance of both wired and wireless is summarized for comparison in Table I. The four parameter values have a great impact on whether an optimum solution is found or the efficiency with which it is found. The  $\alpha$  and  $\beta$  values varied together do not impact the performance. If  $\alpha$  is reduced, the ant system's convergence time increases. The mean was calculated by averaging the number of iterations with the optimal solution obtained. For a wired sensor network, the best parameter set is in the last row of Table I, where the optimal solution was achieved in 120 iterations with a mean value of 16.3187. Similarly, for a wireless sensor network, the fourth row achieved the best results with 125 iterations and mean being 16.4134.

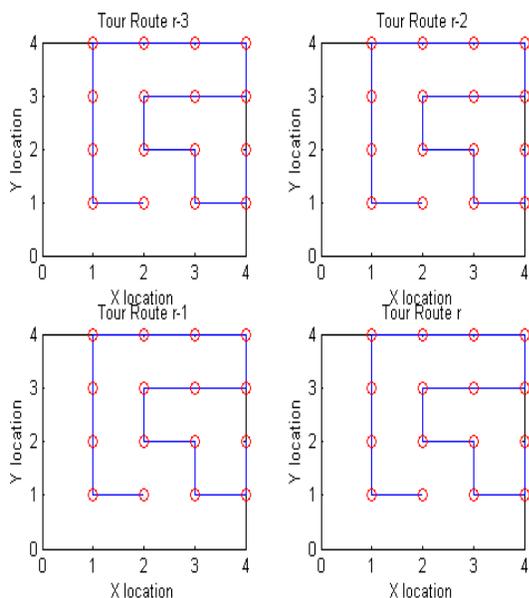


Figure 8. Optimal route in Wireless Sensor Network - with 16 Nodes using Ant System [Q: 0.9 Rho: 0.7 Alpha: 4 Beta:7]

exhibits the behavior of a system that has not converged yet. Figure 8, in contrast, plots four consecutive tours that are identical in performance. This system has found the minimum distance tour.

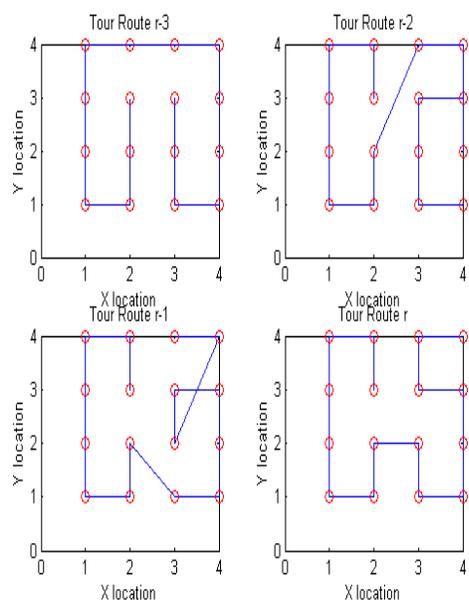


Figure 9. Optimal route in Wired Sensor Network - with 16 Nodes using Ant System [Q: 1 Rho: 0.7 Alpha: 4 Beta:7]

TABLE I. PERFORMANCE vs. PARAMETER IN ANT SYSTEM

Vary	$\alpha$	$\beta$	$\rho$	Q	Mean Optimal Solution in Wired Network	Mean Optimal Solution in Wireless Network
Initial	4	5	0.7	0.9	15.9200	15.5267
Vary $\alpha$	2	5	0.7	0.9	15.7098	15.6716
	7	5	0.7	0.9	15.4031	15.8595
Vary $\beta$	4	7	0.7	0.9	16.8454	16.4134
	4	2	0.7	0.9	16.3328	16.5602
Vary Q	4	5	0.7	0.5	15.8193	16.1464
	4	5	0.7	1	16.2478	16.2759
Vary $\rho$	4	5	0.9	0.9	16.1473	16.6904
	4	5	0.5	0.9	16.3187	16.1061

The ant system is very sensitive to parameter changes especially when more than one is changed. This ant system does balance the distance and the energy dissipation of the sensors. Also the degree to which the parameters  $\alpha, \beta, \rho$  and Q affect the system is shown in this paper. The AS algorithm does successfully find the global optima rather than the local optima. Careful parameter selections can avoid stagnation behavior.

In the future, this AS algorithm will be extended to cover more heterogeneous networks as well as different performance concerns. The networks will consist of a mix of wired and wireless nodes. Irregular spacing of nodes will be investigated. Other performance parameters such as compute energy will also be incorporated.

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