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A Predictive Sensor Network Using Ant System

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ABSTRACT

The need for a robust predictive sensor communication network inspired this research. There are many critical issues in a communication network with different data rate requirements, limited power and bandwidth. Energy consumption is one of the key issues in a sensor network as energy dissipation occurs during routing, communication and monitoring of the environment. This paper covers the routing of a sensor communication network by applying an evolutionary algorithm - the ant system. The issues considered include optimal energy, data fusion from different sensor types and predicting changes in environment with respect to time.

Keywords: Communication, Swarm Intelligence[1], Ant System, Data Mining[2, 3], Sensor Network

1. INTRODUCTION

A building consists of a sensor network with a multitude of wireless communication links and the sensors are interconnected by means of RF communication links. The functionality of nodes in this application include sensing, collecting and distributing dynamic information within the network. Energy usage is a key issue as the sensors are typically tiny and wireless with limited memory and functionality given the fact that the batteries(y) have a limited power supply hence difficulties arise during computation[4]. The communication links in such an unpredictable environment (node failures) are kept functional by applying a robust routing algorithm. The Ant system is a learning algorithm with characteristics such as robustness and versatility solves any NP hard communication problem. In this paper a novel approach is proposed. The agents use the sensor node's information to determine patterns to predict or anticipate changes in the environment with respect to time.

The swarm agents are distributed along the network, where the agent communicates with its neighbors (agents). The current information on energy usage, prediction and decisions concerning environmental situation assessment are made possible by these swarm agents. Another optimization issue is the communication delay. During individual node failure, the swarm routing, unlike some other types of routing, automatically reroutes messages around node failures. The only data lost is data that was last prepared by the node or collected and processed by the failed node. The new route is determined by applying the link status to the ant routing algorithm and other factors depending on the performance parameters including energy and distance. An evolutionary algorithm may not always provide the best global solution but does find the best local decision. Optimality[5], finding the solution that finds the best performance, and reachability[5], the global optimal is found instead of the local optimal, are the two important factors in choosing an appropriate algorithm. The focus of this paper, is to determine patterns using sensor node's information to predict or anticipate changes in the environment with respect to time. In the second section, the justification for using ant system and its impact on the sensor network is discussed. Section 3 discusses data mining and its importance in making predictable decisions to improve the performance of the network. Simulation results provide an insight of real-time situation assessment are provided in the fourth section. The paper concludes with the fifth section discussing the conclusion and future work.

2. Swarm Intelligence And Ant System

Swarm Intelligence, is an algorithm that models the collective behavior of social insects, namely the ants, bees, birds, slime mould, etc. Ant system is one such evolution from the swarm intelligence forming an evolutionary algorithm with unique characteristics such as robustness, distributed problem solving, versatility and de-centralized approach. The ant system solves any complex optimization problem involving many complex and heterogeneous nodes. It also adapts to the network with environmental changes. The agents in the system communicate interactively either directly or indirectly in a distributed problem-solving manner. In this paper, the ant system is applied to a building sensor network with wireless sensor nodes.

The agents move towards the optimal solution and communicate directly by sharing knowledge with their neighbors. The initial set of agents traverse through the nodes in a random manner, and once they reach their destinations, they deposit pheromone trails as a means of communicating indirectly with the other ants. The pheromone accumulation is proportional to the number of agents traveling between two nodes during one complete iteration. The amount of pheromone left by the previous ant agents increases the probability that the same route is taking during the current iteration. Other performance factors discussed also affect the probability of selecting a specific path or solution. Pheromone evaporation over time plays an important role in preventing suboptimal solutions from dominating in the beginning.

There are three different kinds of ant agents, which performs functions such as allocating, sensing and de-allocating the sensed values. Thus, no values are fed into the system other than the initial values. In the system, the agents minimize energy and keep track of network requirements. The allocator agents monitor the allocation process on active links and allocate resources required by the network. The sensing agent's function is to traverse the network and communicate with its neighbors to reach the destination using an optimal route. The deallocator agents are responsible for deallocating trails identified by the sensing agents with the sensed values. As the ant moves from node to node, energy is lost through communication. The ant stops traversing a node once its energy is depleted. New paths are set up to avoid the node so that communication continues without the degraded sensor. These agents ensure that the optimal route to the destination using limited resources and also learning the network environment. Initially, the computational cost and time is high but this drops drastically once the agents learn the network and environment

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 nodes in the network depending on the number of hops assigned by the user. Thus traversing all the nodes and depleting all the energy at every node is avoided. 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.

2.1 Ant System in a Building Sensor Network

Figure 1 shows a sensor network incorporated for a four-storey building layout. The circles denote sensors, which are placed in the rooms. The number of rooms in the building is independent of the number of sensors. The environment inside the building is monitored for safety as well as security purposes. For instance, sudden raise in temperature in any room or hallway indicates an emergency situation, so assessing the situation and monitoring all movement in a building proves valuable. The amount of false alarms can also be reduced by fusion of data at sensor nodes. The nodes help in transferring effective data for making decisions. The energy of each sensor and their communication strength varies depending on the presence of any major obstacles in the routing path

Fig. 1.Four storey building layout with wireless sensors

A suboptimal tour is represented in Figure 2 with circles denoting the nodes and the lines denoting the paths taken by the ant agents between the sensor nodes within a floor. The dotted arrowed lines represent communication between floors in the building. Floors 1, 2, 3 and 4 are spread with 6, 7, 6 and 6 sensors, respectively. In each floor, the source and destination nodes are varied but the number of hops 5 remains constant. Communication among nodes between

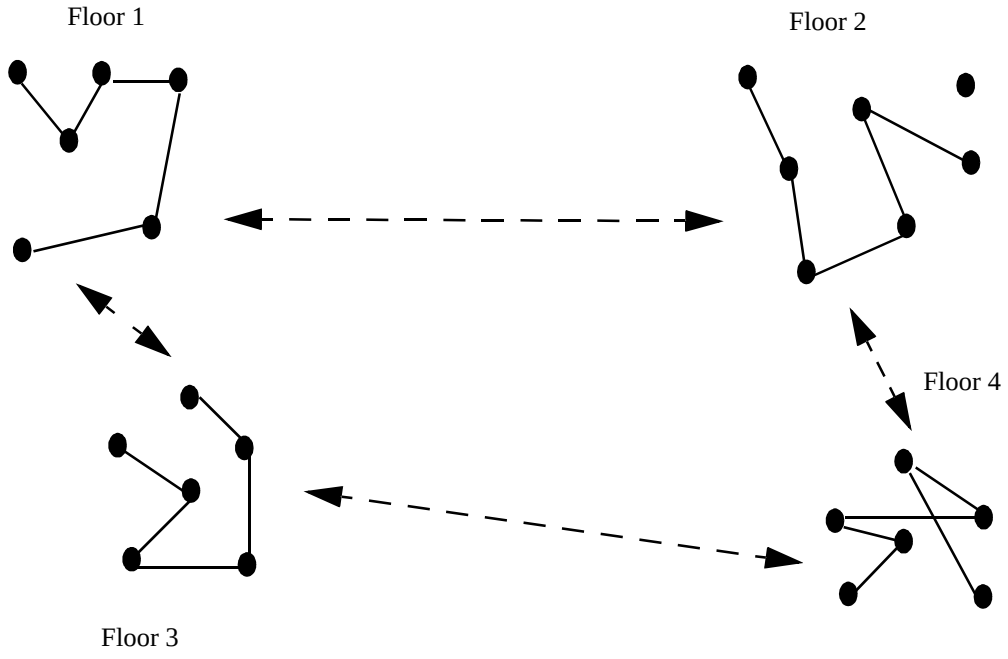

Fig. 2.Suboptimal routes taken by the ant agent upon traversing sensor's in the building

floors is proportional to the strength between the links. Hence, there are no cluster heads in the sensor network. The node locations are represented in dimensional cartesian coordinates for this simulation. The nodes are initially assigned with random energy value.

Three key elements in this AS include the pheromone deposition, energy tracking, and tabu list maintenance. There is a loss of energy that is the reciprocal of the distance between the nodes travelled by the agent. The tour begins at the specified source node in the Figure 2 and ends when a route is complete in regard to the number of hops and finally reaching the destination node. In a given tour, a node is never re-visited. A particular node could be ignored if the fused information is found in the neighboring node or if the number of hops is achieved. The Tabu list contains a record of the path taken by each agent. The pheromones are updated and the list is cleared after completion of each tour. The change in pheromones is a function of the amount of pheromone deposited on the path, the total distance travelled by the agent and the weight applied to the mined information of the link status. The mathematical approach of the ant system in a building sensor network is given in detail in the following section.

2.2 Mathematical Approach Of the Ant System

The performance of the AS is determined by the node spacing and 4 parameters: Q is an arbitrary parameter, ρ, controls trail memory, α is the power applied to the pheromones in probability function, and β 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. The Euclidean distance $D_{ij} = \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}$ where i is the source node, j is the destination node, and (X_i,Y_j) 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 value of 10. The pheromone is updated following each complete tour by, (AS - see [7, 8, 11, 12])

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

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 wireless network is computed from with its neighbors (agents) by means of pheromone deposition and tabu list

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

The energy is dissipated from the sensor node after each ant passes through that node. Assumption is made that the wireless nodes consumes more energy than of a wired network. Thus the distance is squared and the energy for a wireless sensor node is given by,

$$\Delta E_{ij} = \frac{K}{(D_{ij})^2} \tag{3}$$

The link budget k, is calculated with respect to the bluetooth protocol i.e., where P_{tx} is the transmitted power, G_{tx} and G_{rx} are the antenna transmit and receiver gain, L_{fs} is the propagation loss and P_{rx} is the receiver sensitivity.

$$P_{tx} = P_{rx} - G_{tx} + L_{fs} + Fadem\arg in \tag{4}$$

The node's remaining energy is computed by

$$E_i(t) = E_i(t-1) - \sum_j \Delta E_{ij} \tag{5}$$

The agents avoid visiting nodes with depleted energy by determining alternative routes in the sensor network. Thus the network remains partially functional even if some individual sensors fail. The tabu list supports energy usage prediction and decisions concerning situation assessment. Transition probabilities assist in optimizing route selections. The above features of the ant system coupled with data mining enhances the predictive nature of sensor network as discussed in the future sections.

3. DATA MINING & SENSOR NETWORK

Data mining is the result of natural evolution of information technology. A non-trivial extraction or mining knowledge of previously known and potentially useful information from a collection of data set. Data mining is applied in many fields for valuable information assessment[13]. In this paper, a sensor network where decision is one of the key factor for any action to take place, it plays a vital role in situation assessment. Data mining works with different kinds of databases, for a network analysis spatial and heterogeneous datasets are used.

3.1 Data Mining With Ant System

The computation complexity of data mining for large database is O(np3), where n data points and p is the associated measurement. Thus the need for a global optimization becomes necessary. There are many algorithms combined

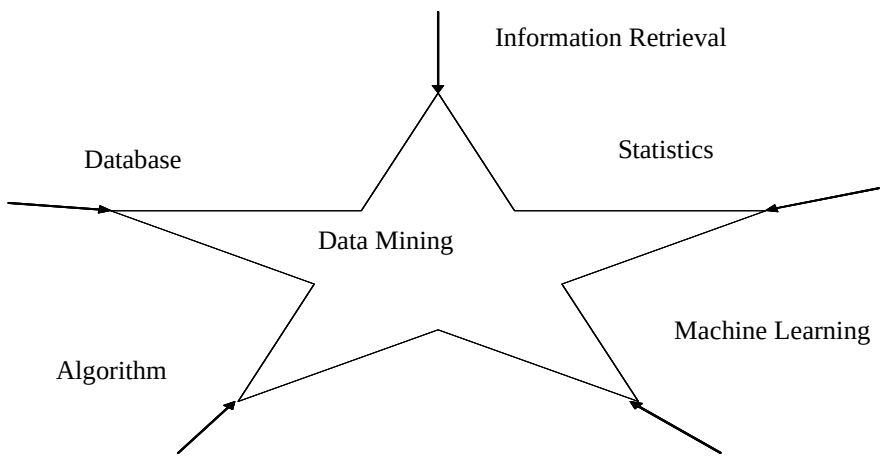

Fig. 3.Data mining as a confluence of multiple disciplines

with data mining to obtain optimal solutions, one such evolutionary algorithm is ant stem (AS). The probabilistic way of obtaining a solution has proven better for large and complex databases.

The rules used for mining the data from the data set is performed by the AS. Using the updated information on the energy depletion and physical distance between nodes the link status can be predicted. The agents deposit the pheromones on the path which is proportional to the predicted link status. The pheromone value corresponds to the greater probability of choosing a stable route. The obtained solution is added to the empty list, which in other words is the tabu-list with the link status. The mined data stored in the tabu-list serve as a base for future data analysis.

4. Predictive Sensor Network Using Ant System and Data Mining

The sensor network with 9 nodes in each floor is considered, with the suboptimal route of a single floor as given in Figure 4. Data fusion[14] occurs at each node so that the environment information is always current. In addition, the agents use sensor node's information to determine patterns that are used to predict or anticipate changes in the environment with respect to time.

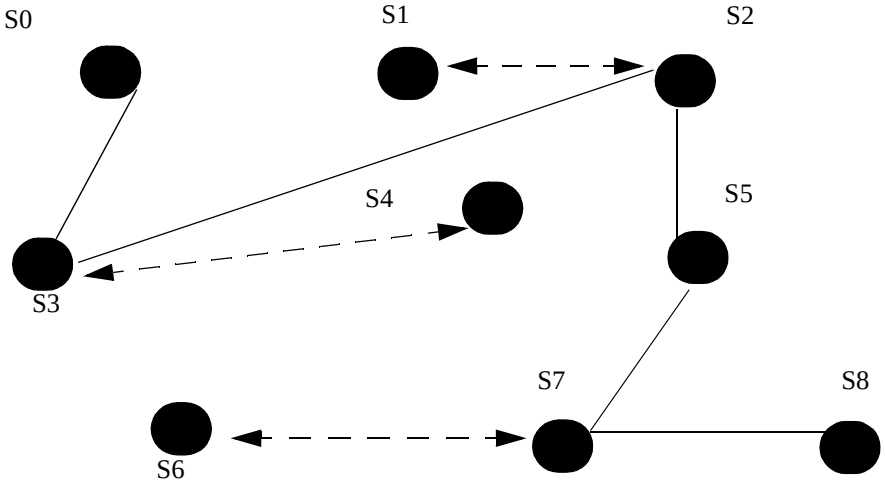

Fig. 4.Predictive Sensor Network Using Ant System and Data mining

The number of hops assigned for this network is 5. The route taken by the agent1 denoted by bold lines is among nodes S0, S3, S2, S5, S7 to S8. The fusion of data is denoted as dotted arrowed lines between nodes S1 and S2 ignoring S1, the data at S4 is fused with S3 eliminating S4 out of the route. The fusion of data between S6 and S7 eliminates S6 out of the communication path. The fused data provides precise information about the particular environment under the sensor's line of sight. The fused data also helps in making simple predictions for data mining rather than increasing complexity in data set.

4.1 Detailed Approach - Predictive Sensor Network

The Sensor network is made predictive, robust and versatile by applying ant system and data mining, which provides effective situation assessment. The probabilistic approach of the ant system depends on the energy depletion and the percentage of false decision. The two factors need to be minimal.

Figure 5 provides a pictorial description of the algorithm used in making a predictive sensor network. The manual operation involved in this network is the definition of the building layout, the sensor equipped in each floors and the initial parameters used in the ant system. The number of agents is proportional to the number of sensors used in the building sensor network. The ant agents are randomly placed on the sensors, not all sensor nodes are assigned an agent. The agents are iterated till the user specified criteria is reached.

As discussed in the second section, the three key elements of the ant system play an important role in making the network robust and de-centralized. The information on the resource availability at any node helps in predicting the link for the agent's next visit.

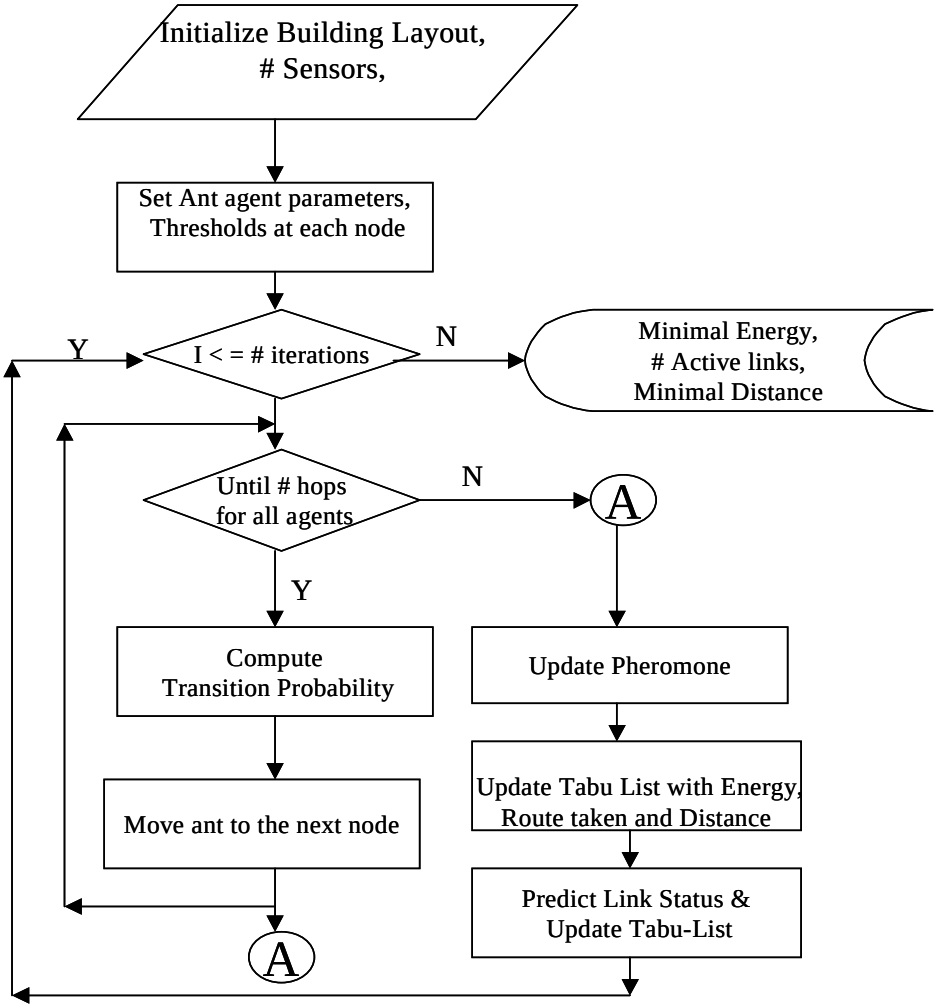

Fig. 5.Flowchart - Predictive Sensor Network

The transition probability is the key factor for making decisions. Weights on each of the factors affects the movement of the ant agent in the network. Link factor is incorporated into the ant system. The transition probability is given as

$$P_{ij} = \frac{((\psi_{ij})^{\alpha} \cdot (Hop_{ij})^{\alpha} \cdot (E_{ij})^{\alpha} \cdot (Link_{ij})^{\beta}) \cdot \left(\frac{1}{D_{ij}}\right)^{2\beta}}{\sum_{k} ((\psi_{ik})^{\alpha} \cdot (Hop_{ik})^{\alpha} \cdot (E_{ik})^{\alpha} \cdot (Link_{ik})^{\beta}) \cdot \left(\frac{1}{D_{ik}}\right)^{2\beta}} \tag{6}$$

where $Link_{ij}$ is the normalized link status as in (7). Hop_{ij} (8) is the normalized value of the total and actual hops taken in a route. The two factors help in making decisions while traversing the data set formed by the agents.

$$Link = \frac{(TotalLinks - \dot{U}nhealthyLinks)}{TotalLinks} \tag{7}$$

$$Hop = \frac{(Totalhop - \dot{A}ctualHop)}{Totalhop} \tag{8}$$

The link status in a tour taken by an agent is incorporated in the pheromone (9). Thus the trails formed by the ant agent is now dependent on the link factor. The pheromone deposition is defined as

$$\psi_{ij}(t) = \rho(\psi_{ij}(t-1)) + \frac{Q}{D_t \cdot E_t \cdot Link_t \cdot Hop_t} \tag{9}$$

The tabu list now consists of updated values of the energy available in the nodes for the particular sub-optimal route with high reachability.

4.2 Result

A sensor network with 16 nodes is considered in this simulation run with agents randomly placed on the nodes. After converging, the ant agents adapt to the network using the knowledge acquired from their neighbors. The table below illustrates six scenarios where the predictive nature of the algorithm is used for assessing the performance of the network.

The parameters of ant system are assumed to be $\alpha = 4$, $\beta = 7$, $\rho = .7$, $Q = 9$ and initial pheromone value, ψ as 10. The number of agents employed in the network is 16, and the source and destination nodes were assumed constant. The stability of the algorithm is analyzed by iterating all scenarios for 100 runs.

The total hops for all the simulations given below is assumed to be 16 which is the number of nodes in the network. The actual hops is user defined which varies depending on the problem assigned. The normalized value of hops is given as $Hops_{Norm}$. The total number of links in the network is equal to the total hops in the network. The normalized link value is given as $Link_{Norm}$. The predicted energy and distance helps in making a decision whether the nodes in the current route is still capable of communicating with its peers in the next iteration.

Table 1 shows the performance of the sensor network where two link failure is estimated. The actual hop is set as 1 with 2 unhealthy and the predicted energy obtained is 82.664. The very high energy prediction leads to a lesser probability of the route to be chosen. In the worst case, where the actual hop is 10, total links is 14, the predicted energy is 43.909. Hence the probability of choosing this route is very high. Thus the network is kept functional even at the worst case.

Table 1. Performance of Sensor Network - Link Failure - 2 Nodes

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predicted Distance	Predicted Energy
16	1	0.9375	16	2	0.875	20.1465	82.664
16	2	0.875	16	2	0.875	18.8406	76.658
16	4	0.75	16	2	0.875	22.3657	74.254
16	6	0.625	16	2	0.875	21.6523	51.526
16	8	0.5	16	2	0.875	23.7393	47.771
16	10	0.375	16	2	0.875	23.9534	43.909

The unhealthy links are rounded to the highest value with respect to the actual number of hops involved to enforce 50% link failure as shown in Table 2. When half of the unhealthy links is equal to the actual number of hops 4 and 6, the energy for the next route is predicted falls between 43.528 and 47.147 respectively. As the number of unhealthy links are increased with respect to the actual number of hops, the energy predicted is also reduced. Thus for a minimal unhealthy link the predictive energy is 62.785. The number of hops plays an important role in leading to a reduced predictive distance and energy. Under a high predictive distance and reduced predictive energy, even the 50% link failure could be overcome.

Table 2. Performance of Sensor Network - Link Failure - 50%

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predictive Distance	Predictive Energy
16	1	0.9375	16	1	0.9375	21.3592	62.785
16	2	0.875	16	1	0.9375	23.6468	55.212
16	4	0.75	16	2	0.875	20.5850	43.528
16	6	0.625	16	3	0.8125	18.4669	47.147
16	8	0.5	16	4	0.75	24.2436	48.059
16	10	0.375	16	5	0.6875	20.9937	55.934

Table 3 gives the performance of the sensor network where the distance between all the nodes is evenly distributed. The equi-distant node placement results in uniform energy dissipation among the nodes. When the link failure was estimated as 50%, as the nodes where equi-distant, the distance predicted remains a constant at 15. There is only a slight energy variation with respect to the number of actual hops. Hence for a equi-distant network even when most of the link fails the performance of the network remains better.

Table 3. Performance of Sensor Network - Distance Evenly Distributed- Link failure - 50%

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predictive Distance	Predictive Energy
16	1	0.9375	16	1	0.9375	15	45.301
16	2	0.875	16	1	0.9375	15	44.694
16	4	0.75	16	2	0.875	15	44.564
16	6	0.625	16	3	0.8125	15	45.722
16	8	0.5	16	4	0.75	15	44.630
16	10	0.375	16	5	0.6875	15	45.529

Table 4 gives the performance of the sensor network where the distance between all the nodes are unevenly distributed. Hence, the performance of the network is counted towards all the three factors distance, energy and link status between the sensors. As the nodes are placed at random, the energy dissipation between the nodes is also random. Hence, the number of link failure is assumed to be 50% with fusion between nodes that have healthy communication links but not included in the route. When the actual hop is 4 and the number of healthy link is 13, the predictive distance and energy is 22.1076 and 62.439 respectively. The unevenly distributed network fails to function when the number of unhealthy link is increased to 8. The predictive distance though being minimal 21.9813 results in very high predicted energy of 85.696, that the route becomes inefficient for traversing.

Table 4. Performance of Sensor Network - Distance Unevenly Distributed - Link failure 75% - With Fusion

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predictive Distance	Predictive Energy
16	1	0.9375	16	1	0.9375	21.1744	46.741
16	2	0.875	16	2	0.875	24.0675	54.883
16	4	0.75	16	3	0.8125	22.1076	62.439
16	6	0.625	16	5	0.6875	21.1052	47.711
16	8	0.5	16	6	0.625	21.1318	53.028
16	10	0.375	16	8	0.5	21.9813	85.696

Table 5 gives the performance of the sensor network where the energy at each node is evenly distributed. Hence, the performance of the network is counted towards the distance, energy dissipation and link status between the sensors. As all the nodes have same energy level, but random energy dissipation, the link failure could be problem dependent. The problem is made simple by considering only 50% link failure. When the number of unhealthy links is half the number of hops i.e., 1:1 ratio the predictive energy is very high 62.164, 75.145 and 60.061 respectively. For a uniform energy distribution, the communication strength due to energy dissipation at each node varies and may lead to less or high energy prediction with a minimal distance of 19.7592.

Table 5. Performance of Sensor Network - Energy Evenly Distributed - Link Failure 50%

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predictive Distance	Predictive Energy
16	1	0.9375	16	1	0.9375	20.9240	62.164
16	2	0.875	16	1	0.9375	21.6365	46.669
16	4	0.75	16	2	0.875	23.1213	56.104
16	6	0.625	16	3	0.8125	22.5765	43.550
16	8	0.5	16	4	0.75	19.7592	75.145
16	10	0.375	16	5	0.6875	21.7883	60.061

Table 6 gives the performance of the sensor network where the energy at each node is unevenly distributed. Hence, the performance of the network is counted towards the distance, energy and link status between the sensors. As all the nodes have random energy level and also the energy dissipation is unpredictable, the link failure could be problem dependent. The problem is made simple by considering only 75% link failure with respect to the actual number of hops.The predictive energy is very high at 95.05 as the link failure is equal to the number of links available. In a network with 75% node failure, data transfer becomes crucial. In such cases, even if the energy predicted is 86.43, 87.22 with only one node healthy link and 74.09, 75.28 with two healthy nodes, the routing is still made possible.

Table 6. Performance of Sensor Network - Energy Unevenly Distributed - Link Failure 75% - With Fusion

# Total Hops	# Actual Hops	$Hops_{Norm}$	# Total Links	# Unhealthy Links	$Link_{Norm}$	Predictive Distance	Predictive Energy
16	1	0.9375	16	1	0.9375	22.1074	95.00
16	2	0.875	16	2	0.875	20.5627	86.05
16	4	0.75	16	3	0.8125	21.1788	85.43
16	6	0.625	16	5	0.6875	24.5108	87.22
16	8	0.5	16	6	0.625	23.2495	74.09
16	10	0.375	16	8	0.5	21.3214	75.28

5. Conclusion and Future work

This paper proposed a predictive sensor network where energy, distance, number of hops and the link status were considered as the key factors combined in an evolutionary algorithm with data mining. The network under a 75% node failure is shown to be functional indicating the robustness of the Ant system. The six scenarios presented in the result section re-emphasize the fact that a sensor network remains functional and assess the situation under all critical conditions.

The sensor network considered in this paper is made simple with 16 nodes and ant agents. The algorithm works on heterogeneous sensor network by only modifying the initial set up of the algorithm. In future work, the data collected by the sensor nodes is made as a dataset from which both an assessment and suggesting a plan based on the situation could be predicted. A sensor network with predictive nature could be applied to many applications where decision plays an important role such as medical controller, military applications, traffic monitoring and others.

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