Robustness of Predictive Sensor Network Routing in Fading Channels

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ABSTRACT

Sensors and their corresponding communication network operate under a variety of constraints, which make effective and robust network routing challenging. In this paper, an extension to the sensor network routing that takes into account physical layer predictions and models [1] using the ant system is proposed. This paper demonstrates the robustness of this approach under slow or fast fading conditions. Implementation of this algorithm should be able to handle hostile environmental conditions. The performance of the network is evaluated based on the bit rate accuracy and response time of the communication routing agents within the network.

Keywords: Protocols, Fading Channel, Swarm Intelligence[3], Ant System, Energy Efficiency, Data Mining[4, 5], Sensor Network

1. INTRODUCTION

Sensor networks with self organizing techniques that optimize nodes based on their capabilities and energy capacities are best suited for deployment in remote area, where batteries often cannot be recharged. Power efficiency and optimization, power scavenging, are the only approaches viable in such an evironment. A sensor network with capabilities such as efficient routing, healthy prediction and self-healing is preferrable. This is the focus taken in this paper.

Sensor networks, which distribute dynamic information, consisting of a multitude RF links and sensor nodes, which include sense and collect this information. Energy is the major constraint of the sensor network. Number of nodes, algorithm complexity, and memory are all functions consuming power [6]. The challenges faced by this network are optimization and load balancing of the communications based on priorities and constraints. This optimization problem is an Nondeterministic Polynomial (NP) hard problem [18]. The Ant system is a learning algorithm which compares local with global optimization information giving it robustness and versatility to solve NP hard problems.

Similar to the deployment of the sensor node, the ant agents are randomly placed along the network. The agents communicate with neighbors (agents) to obtain an optimal solution using the current node status and the information gained through previous routes. The decision on validity of the route is obtained from pheromone deposition by the agents accumulated over time. There are many QoS issues associated with the physical layer of a network. The type of modulation scheme, coding scheme, and queueing impacts the energy exploited for communication. And also communication delay plays a major part in a routing protocol. The amount of time taken for recovering from any data loss or re-routing information during link failure is a tedious task. Unlike other routing algorithms, swarm agents react immediately upon sensing changes in the environment. This feature of the swarm agents truly make it an cognitive algorithm. The only data lost is the one that was prepared by the most recently visited node. Using the updated link status and the performance parameters, the agents exert a random movement towards its destination.

The two main factors that define an evolutionary algorithm are optimality and reachability[14], which draw the boundary between a global and local optimal solution. Although an evolutionary algorithm may not achieve a global solution, a local optima is feasible under adverse conditions. The main focus of this paper is the performance of predictive sensor network under different fading conditions. Modulation schemes such as direct sequence spread spectrum - binary phase shift key, DSSS-BPSK, and frequency hopped spread spectrum - Gaussian frequency shift key, FHSS-GFSK, are compared based on the two main features: energy efficiency and resilience. In the second section, the evolutionary algorithm (ant system) chosen is compared with the genetic algorithm mainly focusing on its characteristic features. Section 3 focusses on the physical layer, and research challenges faced by the sensor network. Simulation results in section 4 are presented including a discussion of the predictive sensor network's robustness under varied fading effects. The paper concludes with the fifth section discussing conclusions and future work.

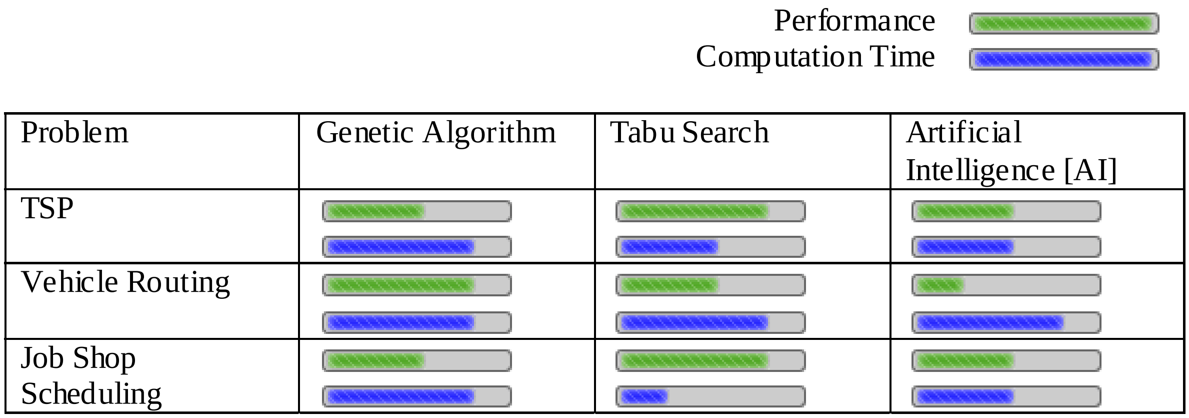
2. Evolutionary Algorithm - Ant System & Genetic Algorithm

Evolutionary algorithms (EA) are formulated based on phenomena found in nature. Two such evolutionary algorithms are the genetic algorithm and the ant system. The former is inspired by using simple genetic evolution of a living being, and the latter is inspired by studying the behavior of ants. The genetic algorithm (GA) was developed in the 1970's by John Holland at University of Michigan as a method to solve optimization problem. Swarm intelligence (SI) is an EA that uses artificial intelligence (AI) techniques. SI demonstrates the collective behavior of social insects, namely the ants, bees, birds, slime mould, etc. In the early 90's, studies on optimization techniques using analogies based on swarm behavior of natural creatures had been conducted. Ant systems (AS) evolved from SI, and its key feature is the emergent behavior of the autonomous agents. Both GA and AS are specialized in their own ways for solving discrete, continuos and hard combinatorial optimization problem. The algorithm chosen for any problem is primarily application dependent.

G'omez in [7] provides reasons for the success of Ant Colony Optimization (ACO) in comparison to GAs on the Travelling Salesman Problem (TSP) benchmark problem, a famous NP hard problem. Table 1 summarizes performance comparisons of the various algorithms with respect to these benchmark NP hard problem. The TSP solution space has a globally convex structure [12]. The presence of one dominant solution in GA results in a behavior like a single point search algorithm. GAs can easily produce a local solution rather than a global solution. Therefore when multiple solutions dominate a particular problem's population, the reduced diversity of GA may result in an errored solution. Thus, GA falls short in situations like this where ACO, using positive correlation approaches where promising solution is located, may easily succeed.

In Table 1, the algorithms are compared with respect to their performance and computation time based on the analysis in [8, 9, 10, 11]. The performance is given by the green bar varying from 0-100%, and the red bar denotes the computation time. Success of an algorithm is defined as attaining the optimal solution. The computation time is defined as the amount of time the algorithm takes to obtain an optimal solution. Though GA finds an optimal solution, the computation time taken in achieving best results is very high, and, hence, the GA approach falls short. Whereas, the Tabu search technique rarely falls into a local optima without finding the global optima with less processing time making it a competitive alternative to GA. In some cases, a combination of artificial intelligence such as a bayesian network and any of the evolutionary algorithm achieves better result. It is shown that an algorithm is not chosen based on performance only but also on the processing time. A trade-off between factors affecting the overall performance of a system is primarily application dependent.

Table 1. Overall Performance of Ant Approach in comparison to other algorithms



In this paper, a sensor network deployed in a remote area is considered, for example, a military application. Thus, the sensitivity and performance of the information processed is very high. There are many routing algorithms such as shortest path, centralized, distributed and flow-based. The complexity of each algorithm focusses mainly on the performance measure used. A military application by nature requires self organizing, distributed and dynamic network. Hence, based on the nature of the problem, an evolutionary algorithm is preferred in comparison with traditional algorithms.

The sensor network considered here is made of decentralized nodes with limited resources, whose topology, information and network size are dynamic with respect to the environment. Henceforth, the performance metrics such as bandwidth, network throughput, communication delay and other constraints are traded off depending on the algorithm used. SI’s characteristics such as scalability, fault tolerance, adaptation, speed, modularity, autonomy, and parallelism [13, 14] make it an optimal choice for the predictive sensor network. There has been many versions of the swarm-based routing algorithms such as AntNet, Ant Based Control (ABC) [21], Ant colonies, and Ant-based Routing System (ARS) [22]. The AS exploits features of previously mentioned algorithms as well as adapting to dynamic environments. The agents in the system communicate interactively either directly or indirectly in a distributed problem-solving manner.

In AS, 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 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 such as energy, hops, distance, and bit error rate (BER) 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.

The ant agents are differentiated into three depending on their task such as allocator, sense and de-allocators. Unlike other algorithms, AS does not require any initial solution given to the system. It only requires parameter settings of the agents, constraints posed on the network, and weights given to each of these. The agents traverse the nodes ignoring any depleted node as shared by the neighboring nodes’ current node status information. Thus the network performance is maintained using this learning algorithm. New paths are set up to neglect communication using degraded nodes; These nodes now perform only sensing function and are removed from routing. The initial computational cost and time is high as the agents learn but drops drastically balancing the load optimally over the network.

A Tabu-list is a gradient-descent search based on the memory parameter set at the initialization. The Tabu-list serves as a memory tool listing the set of nodes visited by that ant agent and avoids a circular path or loop from forming. The ant's goal is to visit all nodes in the network constrained by the number of hops. The pheromones on all the paths are updated at the end of a tour by a returning ant. The pheromone deposition, tabu-list, energy monitoring and predicting from stored information are combined in the AS presented, which has improved robustness and gradual degradation.

2.1 Application Using Ant System

Figure 1 shows the wireless sensor network deployed in a remote area with homogeneous nodes. The red nodes denote that the sensors are active (i.e., they are capable of routing and sensing) whereas the blue sensors are inactive; whose energy have been depleted. The green rectangle denotes the beacon nodes, which helps in determining the localization of the sensor nodes. As the network is deployed in a remote area, there are objects such as bridge, mountain, etc. that pose as barrier for communication between the sensors. Other conditions such as folliage, snow, rain, etc may simply degrade the communication signal rather than completely block it. The energy of each sensor and their communication strength varies depending on the geography along the routing path. And, also there is no security enforced on these sensors, hence they are easily compromised.

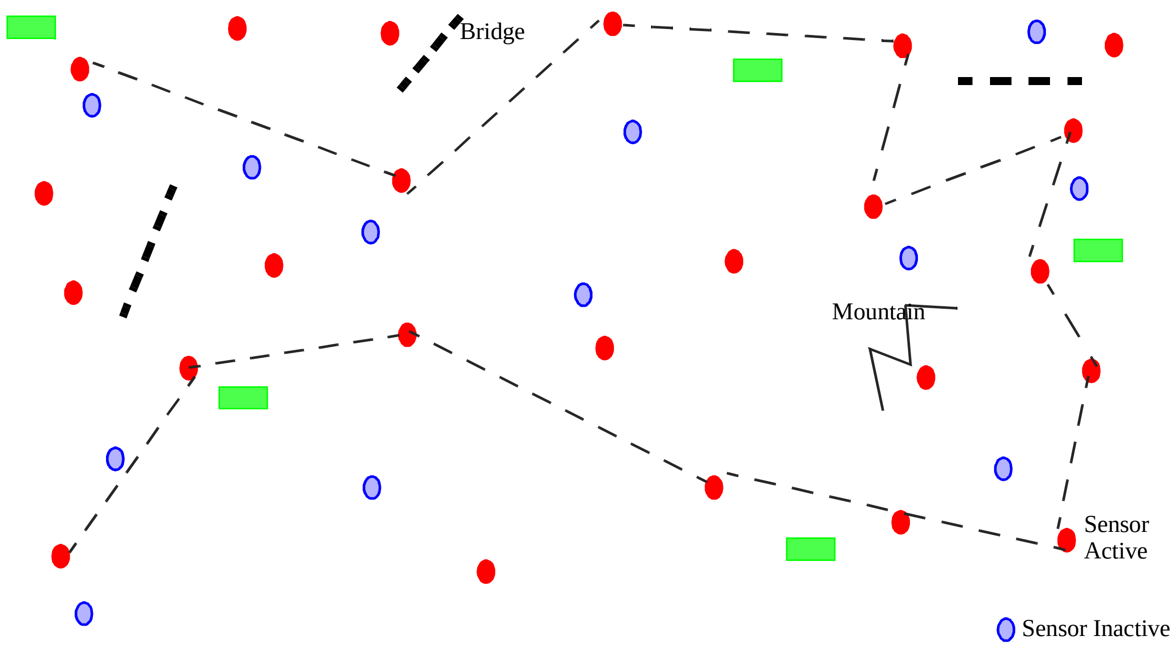


Fig. 1.Wireless Sensors deployed in a remote area

The assumptions for this simulation include the node's awareness of their approximate location by testing the signal strength during their initial deployment. Secondly, the sensors schedule their sleeping time so that its neighbors take over for it. If there are no neighbors, the sensor does not participate in routing saving energy. Messages are received and routed to a neighboring node with an updated time from the sensor's clock and additional data from the sensor if available. Depending on the sensor's id and clock time, duplicate information can be easily identified and omitted. The sensors are non-uniformly distributed, and their locations are represented in dimensional cartesian coordinates for this simulation. The nodes are initially assigned with random energy values.

Using features such as pheromone deposition, energy tracking and tabu list maintenance, routing in an adverse environment is possible due to the local information available. The energy dissipated is estimated by the total distance travelled by the agent, which move from node to node. The agents are randomly placed on the nodes initially. When triggered by an event such as the sending of a prioritized message, the agent quickly routes the data to the proper destination node within the maximum number of hops. As mentioned above, no circular paths are allowed preventing a node from being re-visited. 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 parameters used in the ant system is given in detail in the following section.

2.2 Parameters Of the Ant System

The performance of the AS is determined by the node spacing and 4 parameters: Q, ρ, α and β [6]. The complexity of the AS algorithm depends on transferring the routing information between agents and updating the table in a timely fashion. The network configuration parameters are relatively weighted depending on a real time scenario. The nodes are spread across a 2D plane. 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 a value of 10. The messages are routed based on their importance, thus differentiating them into high, medium and low threats. The transition probability is now associated with a new factor, the threat probability Γ_{ij}. of the pheromone, and transition probability in [2, 8, 10].

3. PROTOCOLS

The physical layer of the predictive sensor network [2] is being extended to affect routing if the OSI-ISO terminology is considered. The decentralized sensor nodes will route the information by means of protocols such as IEEE 802.11b and Bluetooth GFSK as used in this paper. The sensor nodes are assumed to be lightweight, 41g, with antenna and a data rate of 11Mbps. There are many IEEE Standards available in the market, but zigbee based on IEEE 802.15.4 standard is quite popular for simple sensors in a sensor networks. A comparison between AS's performance using FHSS_GFSK and DSSS_BPSK modulation scheme is analyzed. The data throughput of FHSS_GFSK and DSSS-BPSK is assumed to be 1Mbps. The models are simulated using Matlab 6.5 and Simulink R13.

4. PREDICTIVE SENSOR NETWORK

A sensor network with 16 nodes is considered with data fusion occurring at each node keeping the information current. In addition, the agents use sensor node's information to determine patterns [19] that are used to predict or anticipate changes in the environment with respect to time. The number of hops is one of the factor that influences the path taken by an agent. Hence, the routing path might include the fused data processed by the routing nodes giving some predictions even when not requested.

4.1 Detailed Approach - Predictive Sensor Network

The predictive sensor network uses the spread spectrum method for keeping the nodes at minimal risk. Rayleigh fading is assumed simulating the challenging environment. Due to the scarcity of power, the memory of the sensor nodes is assumed to be limited and queuing of messages at each node is limited. There are different types of messages in this network such as high threat, medium threat and low threat. The arrival time of these messages is given by the poisson distribution. Henceforth, the transfer of message to its destination node highly depends on the importance of the message rather than arrival time. The number of retransmission attempts are limited so the AS upon detecting a high BER finds an alternate route with minimum BER and good SNR value. The energy dissipated depends on the data type;

as control data consumes higher energy than the message data. From the use of AS, a network with longer lifetime and energy efficiency is achieved by trading off various constraints of the network.

4.2 Pseudo Code - Predictive Sensor Network

Figure 2 provides the pseudo code of predictive sensor network. Once the network is set up, the ant agents are randomly placed on the network with their initial parameters configured to default settings. The simulation is performed for a defined number of iterations or unless a global optimal is reached.

As mentioned in [3], the ant agents work towards the goal in a decentralized manner using their three main features. The number of agents is equal to the number of sensors in the network increasing the ability to find a reliable and efficient route. The performance factor plays a key role for the path selection by the agent. An additional factor Pe, which, is the bit error rate for the corresponding signal to noise ratio (SNR) value is added to the transition probability, P_{ij}. Formulation of (2) shows that the physical layer factors are important in making routing decision for the network layer.

```
Initilization of AS parameters
Initialization of N/w
   for each node
      Generate arrival time
      for each ant
       for each hop
          next node = select (node,destn node, tabu-list,perf factor)
          if msg_priority = high
              break;
            elseif msg_priority = medium
                if msg_atnode > msg_received
                    put msg_on_stack
                else
                  break;
                end if
             else
                  put msg_on_stack;
           end if
        lay pheromones
       end for loop (hop)
        update pheromone deposition, , transition probability
     end for loop (ant agent)
     update tabu-list
   end for loop (node)
```

Fig. 2.Pseudo code - Predictive Sensor Network

Threat messages are routed by the agents upon detection to the destination node within the specified number of hops. The GFSK and BPSK carrier information is encoded using hamming code (15,11) to reduce the number of BER. 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. The transition probability is given as

$$P_{ij} = \frac{(Perf_{ij})^{\alpha} \cdot (\Psi_{ij})^{\beta}}{\sum_k (Perf_{ik})^{\alpha} \cdot (\Psi_{ik})^{\beta}} \tag{1}$$

where $Perf_{ij}$ is the performance factor given by (2), which consist of the normalized value of the hop, BER, link status, and distance. These factors help in making decisions while traversing the data set formed by the agents

$$Perf_{ij} = \frac{(Hop_{ij}) \cdot (BER_{ij}) \cdot (E_{ij}) \cdot (Link_{ij}) \cdot (\Gamma_{ij}) \cdot \left(\frac{1}{D_{ij}}\right)^2}{\sum_k (Hop_{ik}) \cdot (BER_{ik}) \cdot (E_{ik}) \cdot (Link_{ik}) \cdot (\Gamma_{ij}) \cdot \left(\frac{1}{D_{ik}}\right)^2} \tag{2}$$

The link status, hops and BER in a tour taken by an agent is incorporated in the pheromone (3). Thus the trails formed by the ant agent is now dependent on the both the physical and the MAC layer of a network. The Partially ordered sets (POSets) or a user could weight the performance factors. In this paper, the primary goal is to attain less BER value with minimal energy, hence these two factors are weighed more than the number of hops, link status and distance. The pheromone deposition is defined as

$$\psi_{ij}(t) = \rho(\psi_{ij}(t-1)) + \frac{Q}{D_t \cdot E_t \cdot Link_t \cdot Hop_t \cdot BER_t} \tag{3}$$

$$R_t = \text{No of hops} \times \text{fixed processing time} \times \text{time take for traversing the message} \tag{4}$$

The tabu list now consists of updated values of the average energy, BER, distance travelled and the response time as in (4) for the particular sub-optimal route with high reachability.

4.3 Result

A sensor network with 16 nodes is considered in this simulation run. Agents randomly placed on the nodes. It is evident that more numbers of ant agents leads to less computation time and high performance. To ensure fairness, the network consists of equal number of agents and nodes. The table below illustrates the performance of the algorithm when the network undergoes various threats.

The parameters of ant system are assumed to be $\alpha = 4$, $\beta = 7$, $\rho = .7$, Q = 9 and the initial pheromone value, ψ as 10. At the initialization stage, the source and destination nodes are defined and kept constant throughout the simulation. The stability of the algorithm is analyzed by iterating all scenarios for 100 runs.

The total hops for all simulations is assumed to be same as the number of nodes in the network, that is 16. The actual number of 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 difference between the estimated BER for a wireless medium is10^{-6} and the actual BER obtained through simulation is normalized resulting in BER_{Norm}. The predicted BER, energy and distance helps in making a decision whether the nodes in the current route are capable of communicating with its peers on the next iteration.

Figure 3 shows the BER of DSSS-BPSK model for three different threat levels. The BER for high threat is given by red circles, medium threat is denoted by yellow ‘+’ and low threat by green ‘*’ symbols respectively. The BER achieved for high threat is very less compared to messages with low threat.

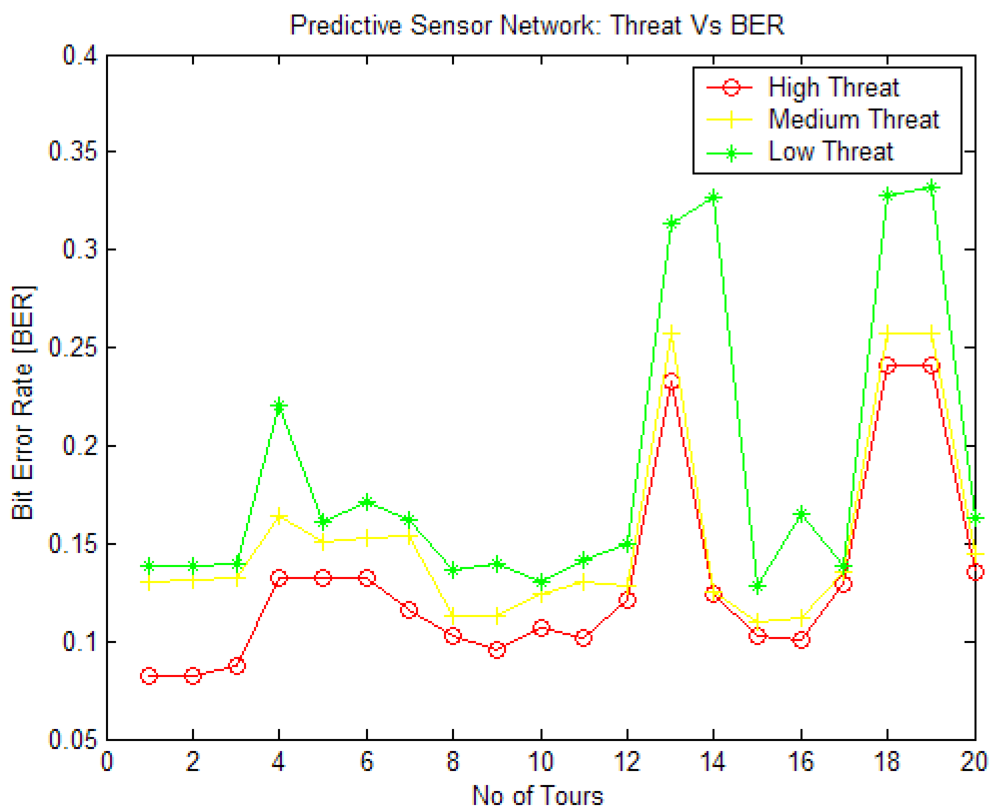


Fig. 3.The BER [DSSS-BPSK] of the Predictive Sensor Network Under various Threat Level

Table 2 shows the performance of the sensor network where two link failure is estimated. The remaining 14 nodes or hops stay active and the number of actual hops is 8 within which the agents must reach their destination. The weights given by the Posets to distance, energy, BER, hops and link status are 0.2, 0.3, 0.3, 0.1, 0.1 respectively. The threat in the network is given random probability ranging from 0-1 for low to high. In the scenario below, the probability for high, medium and low threats are 0.9, 0.1 and 0 respectively. Thus messages with low threat could be routed at leisure. The response time of each of the low threat message undergoes a delay. BER is defined as the product of the Probability of bit error (Pe) and bit rate(Br). The BER_1 denotes the bit error rate of the DSSS-BPSK model and BER_2 denotes the FHSS-GFSK model. Its shown below that the BER_1 is always higher than the BER_2, due to the fact that no error control techniques are used in the former.

Table 2. CASE1: Performance of Sensor Network - Link Failure - 2 Nodes,

Threat	Predicted Distance	Predicted Energy	Predicted BER_1	Predicted BER_2	Response Time
High	10.0939	14.8077	0.6125	0.5263	0.0020
Medium	14.2769	20.2170	0.6750	0.5611	0.0127
Low	26.4425	26.0393	0.7238	0.5941	0.0223

Table 3 shows 50% link failure with 8 nodes in the network have depleted energy. Under this condition, maintaining the BER and energy at minimum is a tedious task. The weights given to the performance factors are 0.1, 0.2 0.4, 0.1, and 0.2 respectively. The threat probability is given by 0.5, 0.5 and 0 for high, medium and low threats respectively. The predicted distance under 50% link failure or with only 8 hops is given by 10.9798. This value is very high when compared to the earlier case of 10.0939. The high value is due to the fact that the agents have to transfer messages to farther active nodes thus attaining a predictive energy of 15.1010 for high threat messages. Similarly, the response time of the agents is also affected. The BER_1 value in this case is lesser than the BER_2, as the hamming code is used in the former and not in the latter. The BER value of case2 is less than BER values of case1, as the weights given by the Poset to BER was higher unlike the previous case. Consider a scenario where the destination node has depleted its energy. In this case, the message regardless of threat level is undeliverable.

Table 3. CASE 2: Performance of Sensor Network - Link Failure - 50%

Threat	Predictive Distance	Predictive Energy	Predictive BER_1	Predictive BER_2	Response Time
High	10.9798	15.1010	0.4188	0.4565	0.0050
Medium	22.0188	23.1060	0.4562	0.481	0.0165
Low	25.1183	28.0492	0.5238	0.5315	0.0288

Table 4 gives the performance of the sensor network where the nodes are evenly distributed. The equi-distant node placement results in uniform energy dissipation among the nodes. The threat probability and Poset weights remains the same as case2 for fair comparison.

Table 4. CASE 3: Performance of Sensor Network - Distance Evenly Distributed- Link failure - 50%

Threat	Predictive Distance	Predictive Energy	Predictive BER_1	Predictive BER_2	Response Time
High	15	17.0801	0.3762	0.4435	0.0096
Medium	15	18.9161	0.4641	0.4717	0.0140
Low	15	20.1020	0.4897	0.4905	0.0211

The predictive distance was kept at constant 15, due to the placement of nodes, this has directly reduced the predictive energy for messages under medium and low threat mode. The response time of the agents is reduced significantly. The time taken to traverse a message in a evenly distributed network is almost the same with little or no delay depending on the message traffic.

Table 5 gives the performance of the sensor network where the energy at each node is evenly allocated. As all the nodes have same energy level, but random energy dissipation, the link failure could be problem dependent. In this case, the actual number of hops is 8 and the weights for the performance parameters are 0.1, 0.2, 0.3, 0.1 and 0.3 respectively. Hence the link status and BER plays a key role in the traversing the network. The primary factor that influences the energy dissipation is the communication strength at each node. The results show that the initial energy distribution has minimal impact on the performance of the network. The communication strength and the energy depletion during the processing stage have higher impact on the network performance.

Table 5. CASE 4: Performance of Sensor Network - Energy Evenly Distributed - Link Failure 50%

Threat	Predictive Distance	Predictive Energy	Predictive BER_1	Predictive BER_2	Response Time
High	16.2546	17.2187	0.4650	0.4636	0.012
Medium	21.1525	21.5486	0.6291	0.5263	0.0171
Low	27.0912	28.2987	0.6746	0.605	0.0230

Table 6 gives the performance of the sensor network where the distance between the nodes are uneven. As the nodes are placed at random, the energy dissipation between the nodes is also random. The link failure is assumed to be 75%. The message needs to be traversed within 4 hops. Fusion between nodes enhances the environment awareness, and also reduces data loss by the depleted nodes. The Poset weights to the link status and number of hops needs to be highly weighed when compared to the other performance parameters. Therefore, the weights are assigned as 0.05, 0.15, 0.2, 0.3 and 0.3 respectively. The predicted energy is double that of the predicted distance because of the amount of energy dissipated in traversing the message to farther nodes. The BER_1 and BER_2 are also affected due to the 75% link failure as the communication strength is low when the nodes are placed farther apart. It must be noted that the response time is too low but when referring back to (3), it is evident that the number of hops leads to a deceiving solution.

Table 6. CASE 5: Performance of Sensor Network - Distance Unevenly Distributed - Link failure 75%

Threat	Predictive Distance	Predictive Energy	Predictive BER_1	Predictive BER_2	Response Time
High	18.8128	27.5297	0.5181	0.5221	0.0066
Medium	24.7391.	42.3806	0.5479	0.5406	0.0170
Low	32.1285	63.3994	0.634	0.6526	0.0227

Table 7 gives the performance of the sensor network where the energy at each node is unevenly allocated. Hence, the performance of the network is counted towards the distance, energy, BER and link status between the sensors. The Poset weights for this problem is the same as the above case. In a network with 75% node failure and with uneven energy distribution data transfer becomes crucial. The energy being unevenly distributed has lead to a great loss of energy but even under this condition the BER_1 and BER_2 were kept at minimal. Threat messages are always given priority and packet losses due to link failure are avoided.

Table 7. CASE 6: Performance of Sensor Network - Energy Unevenly Distributed - Link Failure 75% - With Fusion

Threat	Predictive Distance	Predictive Energy	Predictive BER_1	Predictive BER_2	Response Time
High	20.6538	52.5591	0.5329	0.51	0.0101
Medium	26.0040	63.1376	0.6025	0.5951	0.0126
Low	35.8489	87.3408	0.6493	0.6219	0.0266

5. Conclusion and Future work

This paper extends the physical layer of the predictive sensor network to affect routing where energy, BER, distance, number of hops and the link status are now factors. The major contribution in this paper, is to maintain a low BER under harsh environmental conditions and prioritizing the threat messages. The network under a 75% node failure resulted in a lower BER using both FHSS-GFSK and DSSS-BPSK model indicating the robustness of the AS. 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. In this paper, the secure transmission of data is provided using the spectrum. When an entire spectrum is compromised, DS/FH spread spectrum [20] methodology can be used.

A combination of Artificial Intelligence and evolutionary algorithm increases the performance of the system. Hence, Bayesian network could be introduced, which would further enhance the learning ability of the AS. There are different modes of operation in IEEE802.11 such as Ad-hoc mode and infrastructure mode. The predictive sensor network will be modified to incorporate all these features. The sensor nodes considered here are assumed to be under a secure environment, which is not true in reality. Secure transmission of messages under worm hole and sybil attack need to be considered as future work.

The predictive nature of this approach could apply to many areas of engineering. A sensor network with predictive capabilities could be applied to applications where decision plays an important role such as medical controller, military applications, traffic monitoring and others.

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