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Contents

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Computational Aspects of Sensor Network Protocols (Distributed Sensor Network Simulator)

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Abstract: In this work, we model the sensor networks as an unsupervised learning and clustering process. We classify nodes according to its static distribution to form known class densities (CCPD). These densities are chosen from specific cross-layer features which maximizes lifetime of power-aware routing algorithms. To circumvent computational complexities of a power-ware communication STACK we introduce path-loss models at the nodes only for high density deployments. We study the cluster heads and formulate the data handling capacity for an expected deployment and use localized probability models to fuse the data with its side information before transmission. So each cluster head has a unique P_{max} [10] but not all cluster heads have the same measured value. If the cluster size in n, from the cluster then the first order entropy of data aggregation is

$$H(S) = \sum_{0}^{n} P[(x]_i) \sum_{0}^{n} P[(x]_i) \log P[(x]_i) = 1$$

In a lossless mode if there are no faults in the sensor network then we can show that the highest probability given by P_{max} is ambiguous if its frequency is $\leq \frac{n}{2}$ otherwise it can be determined by a local function. We further show that the event detection at the cluster heads can be modelled with a pattern 2^m and m, the number of bits can be a correlated pattern of 2 bits and for a tight lower bound we use 3-bit Huffman codes which have entropy of

$$\sum_{0}^{n} P[(x]_i) \log P[(x]_i) < 1$$

These local algorithms are further studied to optimize on power, fault detection and to maximize on the distributed routing algorithm used at the higher layers. From these bounds in large network, it is observed that the power dissipation is network size invariant. The performance of the routing algorithms solely based on success of finding healthy nodes in a large distribution. It is also observed that if the network size is kept constant and the density of the nodes is kept closer then the local pathloss model effects the performance of the routing algorithms. We also obtain the maximum intensity of transmitting nodes for a given category of routing algorithms for an outage constraint, i.e., the lifetime of sensor network.

Keywords: Power-aware routing, Sensor network lifetime, MAC layer, Distributed algorithms, Bayesian classifier, Slepian & Wolf theorem, Real-time sensing and simulation, Huffman coding, Entropy

1. Introduction

It has been recognized that energy savings can be obtained by pushing computation within the network in the form of localized and distributed algorithms. A common optimizations used by distributed power-aware algorithms is to select cluster heads or transmitting nodes which allows source, destination pairs to forward data in a multi-hop route. Analytically convenient assumption for the node distribution as shown in Fig. 1, in large wireless networks is homogeneous (or stationary), where the number of nodes in a certain area of density which minimizes communications costs by using a distributed criteria (such as time scheduling, spacial distribution or total power available in the network) and the numbers of nodes in two disjoint areas are independent random variables. For sensor networks, this assumption is usually justified by claiming that sensor nodes may be dropped from aircraft in large numbers. As sensor networks uses self-organizing topology management and the distributed algorithms uses cross-layer energy management optimizations(such as Sleep scheduling, MAC duty cycle, netcoding), the nodes as they are deployed in a one dimensional lattice from source to sink can be easily represented in two dimensions Bayesian classifier. The class conditional probability densities (CCPD) for $\omega 1, \omega 2$ are determined by a priori number of neighbors. This classifier deterministically finds the next source, destination pairs during each iterations of the distributed algorithm due to known probability for successful transmission. To know the error of the classifier (Lifetime) P(error|x), we like to optimize number of classes $\omega 1, \omega 2, \omega 1, .. \omega n$ which maximizes lifetime of the sensor network without faults. If the class conditional densities are not known a priori in unattended Bayesian learning θ then the success of transmission by a sensor node can be modeled as a Maximum-Likelihood estimate, as the power-aware resource ϴ is known it can find nodes which are in the transmitting range. From the comparison of the Bayesian Classifier and the best effort Maximum-Likelihood classifier for using the ideal transmitters, which shows that if n the number of nodes increases then the Bayesian Classifier and the Maximum-Likelihood classifier has the same success probability of transmission. We derive the distributional properties of the interference and provide upper and lower bounds for its CCPD. We show that distributed Bayesian Classifier performs better when the transmitter-receiver ratio is 80 %-20 % the success probability is greater than that of a best effort local algorithm's performance. We consider the probability of successful transmission in an interference limited channel when fading is modeled as Rayleigh and using CSMA and B-MAC. Power losses due to overhearing, interference and fixed radio range induced by MAC clustering makes lifetime of routing algorithms perform poorly for the same number of nodes, power and data throughput.

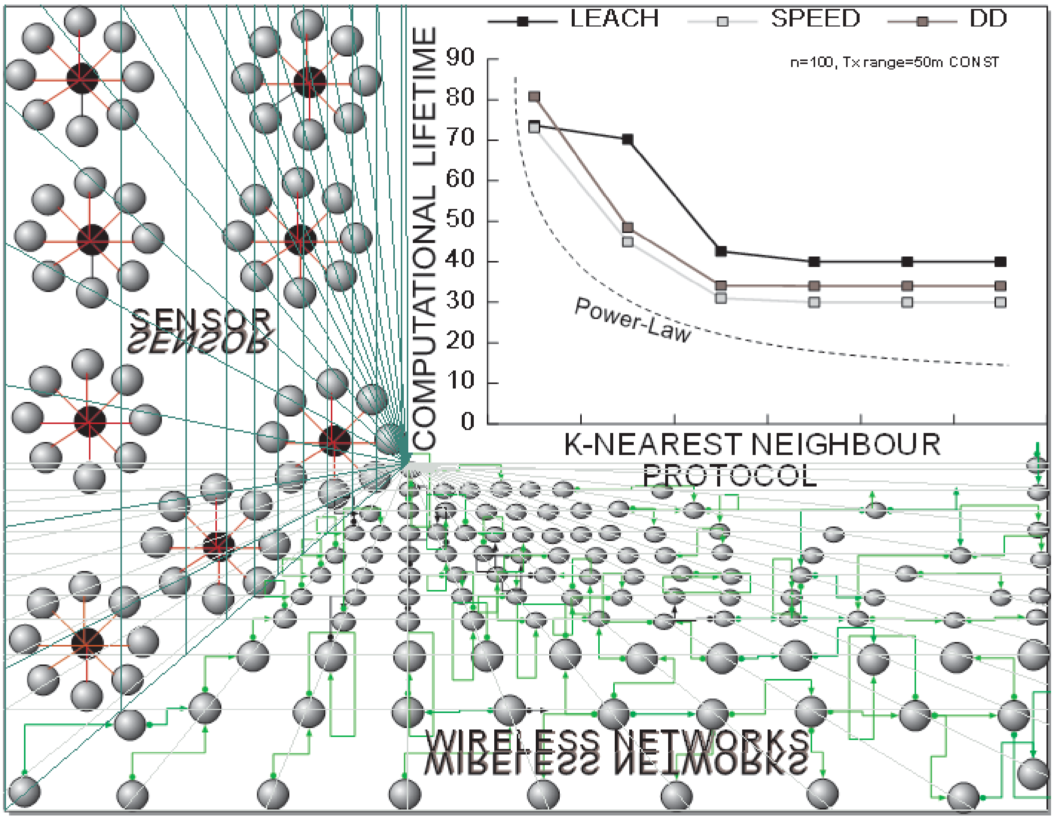


Fig. 1. Computational and Protocol aspects of WSN simulator.

2. Related Work

2.1. Distributed Algorithms

There exists a significant body of literature for cross-layer networks performance using distributed nodes. This is the framework for MIT's μ - AMPS project [12], which focus on innovative energy optimized solutions at all levels of the system hierarchy, from the physical layer and communication protocols up to the application layer and efficient DSP design for micro sensors nodes. Sensor networks contain too much data for an end-user to process. Therefore, automated methods of combining or aggregating the data into small set of meaningful information is required [11]. In addition to helping avoid information overload, data aggregation, also known as data fusion, can combine several unreliable data measurements to produce a more accurate signal by enhancing the common signal and reducing the uncorrelated noise. Here we will categories some of the work done in energy-aware models with respect to reusability (cluster-head) and develop a data fusion framework which allows to avoid unreliable data in any arbitrary size network. Simulations show that LEACH can achieve as much as a factor of **8** reductions in energy dissipation compared with conventional routing protocols. In addition, LEACH is able to distribute energy dissipation evenly throughout the sensors, doubling the useful system lifetime for the networks we simulated. Thus, communication between the sensor nodes and the base station is expensive, and there are no "high-energy" nodes through which communication can proceed.

2.2. Information Processing

Rate distortion theory gives theoretical bounds for how much compression can be achieved using lossy compression methods. Many of the existing audio, speech, image, and video compression techniques have transforms, quantization, and bit-rate allocation procedures that capitalize on the general shape of rate–distortion functions. Rate distortion theory was created by Claude Shannon in his foundational work on information theory. In rate–distortion theory, the rate is usually understood as the number of bits per data sample to be stored or transmitted. The notion of distortion is a subject of on-going discussion. In the most simple case (which is actually used in most cases), the distortion is defined as the variance of the difference between input and output signal (i.e., the mean squared error of the difference).

3. Main Contributions and Organization of the Journal Paper

The journal paper is organized as follows: in Section 4.1-4.7 deals with system model and assumptions which are used in simulation setup and analysis. Section 5.1 deals with algorithmic aspect of distributed selection of cluster head algorithms. Section 6.1 uses simulation for network layer analysis with fixed energy resources for a large sensor networks. Section 7.1 deals with protocol overheads and radio interference model for MAC losses using 802.11/CSMA/BMAC. Section 8.1-8.2 describes aggregation for clustering algorithms using TTL and actual success count for single-hop protocols and multi-hop protocols. It uses the Bit-error ratio (BER) to estimate the capture rate at the receivers and uses fault-tolerant algorithms to design an error resilient codebook. Section 9.1 estimates how sleep scheduling and TDMA based active timeout based MAC helps to increase the lifetime of the sensor network.

4. System Model and Assumptions

In this section we introduce the system model and derive some required results for the cross-layer power analysis. The metrics used in simulation are shown in Fig. 4.

4.1. System Model and Notation

The design of interoperable sensors for the new wireless standards is a task for VLSI hardware and software (firmware) domains. Resource constrained prototypes are hard to deploy and debug so we use a cross-layer simulator due to its unique deployment needs. Such as unreliable wireless channels, remote sensing and non-replenishable energy resource and wastage of energy due to idle and collisions in the underlying protocol. As the sensor application goals is to use a large amount of sensors and use collaborative processing for local tasks. This type of distributed processing not only saves precious sensor's energy but makes is more reliable than using a few nodes and also creates a secure network. Simulator gives a controlled environment to deploy large amounts of nodes and measure faults due to resource bottlenecks at each cross functional layer of the application.

Simulation is performed at each abstraction layer such as energy management, network discovery or point to point communication. The same concepts can be extended to an emulator with common programming methods which once tested can be deployed into hardware running co-resident real-time OS with real drivers and IO's connected. Common goal is to find a micro-OS which interfaces with RS-232, Bluetooth, USB, GPRS or SDIO. This allows transparency to communicate with the external world and allows an easy testing platform with networked PC's. The communication to the PC or a laptop is through a central coordinator node which typically has enough resources and helps manage the sensor network and works as a gateway node between sensing and IP based networks. The coordinator stores all the global parameters which it needs to maintain the network and at the same time manages a data stream with a given communication rate. In contrast to other simulators which give a lot of standard statistics this method allows debugging the resource constraints for custom sensing applications and easily ports into real mote hardware and test their reliability in one common framework.

The architecture combines the upper network layers which solely deal with distributed optimization with the frequent connectivity needs required by the lower layers to achieve balanced performance in terms of energy savings for sensing and routing activity. Since the hardware layers are non-programmable, it is best to use the specification for low cost, low memory and low data rate requirements. The Network-Embedded Test-Bed infrastructure for management and operation of the Test-Bed gives information of the overall running tasks and also supplies management data of the state of the sensors such as expected events, drifting of the clocks, and low resource state indicators. The research presents implementation of different power-aware algorithms and their effects on routing and complexity of implementation.

It uses a JENNET/IEEE802.15.4 ZigBee development platform to validate the memory requirements and target needs used during abstracted simulation. The flexibility in setup allows the target platform to choose according to the needs such as network management, routing or real-time sensing functionality of the OS. This research summary discusses work in progress regarding opportunities and challenges related to cross-level simulation and optimization based on realistic scalable reliability. The cross level approach is shown in Fig. 2, where the baseline architecture is shown in Fig. 2(a) and the respective timing, resource, computation complexity and energy model is shown in Fig. 2(b).

What are the reliabilities which are built-in to the system for such a test-bed? A real-time system responds in a (timely) predictable way to all individual unpredictable external stimuli arrivals. It is important to note that the average performance is not the issue.

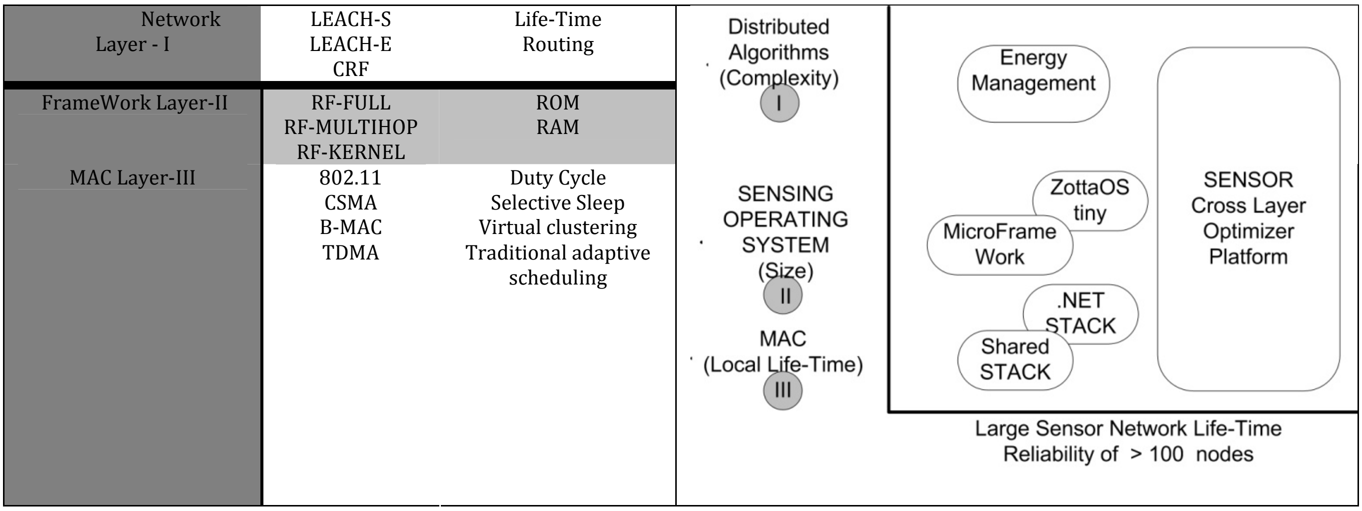


Fig. 2. (a) Cross Layer resource allocation and optimizer, (b) WSN simulator.

4.2. Power-aware Complexity

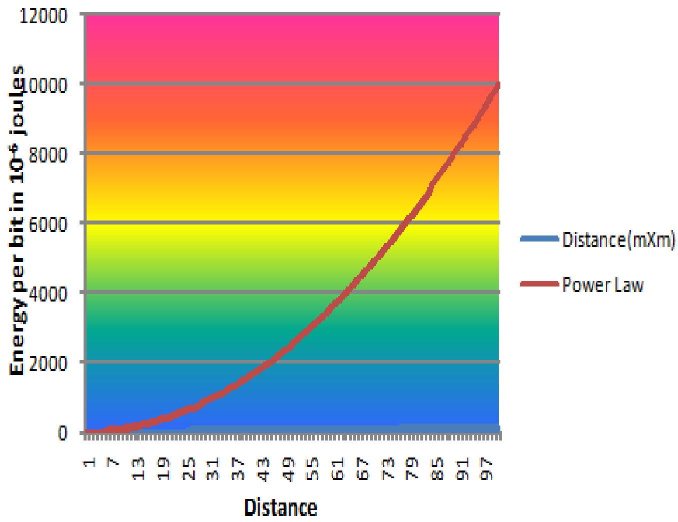
The lifetime of sensor networks is typically factored into the resources it is deployed with, as by design it is unattended (i.e. no replacement of batteries) it coexists for many months to some years. The numbers of sensor nodes are typically run into hundreds to thousands in a large environmental monitoring application. As the number of nodes in such applications are enormous than typical networks it uses a clustering algorithms in which typically 20 %-30 % [8] of the nodes aggregate the data of the remaining 70 %-80 % [8] of the connected nodes. These cluster heads are data concentrators which can be modeled as a device CODEC, compressor/decompressor. The sensors which are attached to the nodes typically sense temperature, humidity and light. It is true, however, that the sensor measurements in the operation region are spatially correlated (since many environmental phenomena are) they tend to be very similar. In a CODEC a probability model is used which gives the highest probability to the most frequently occurred values reported by the sensors within the same cluster. This allows transmitting peak values with least amount of bits as the underlying compression algorithm assigns least number of bit for frequently occurring values. This probability distribution is send with the data values to the central coordinator. So each cluster head has a unique P_{Max} [10] but not all cluster heads have the same measured value. As in recent development of VLSI and MEMS technologies have made it possible to package self-powered sensors and wireless radio components which together is capable of collecting and processing new sensor data for a period of many months to few years without replacing the internal batteries. The miniaturized sensors are sensitive to the available effective range to the energy consumed per bit. The *instantaneous drain* on the internal batteries is evident and the study shows that

$$Energy\ consumed\ per\ bit\ to\ transmit = \frac{100pj}{bit} m^2 \tag{4.1}$$

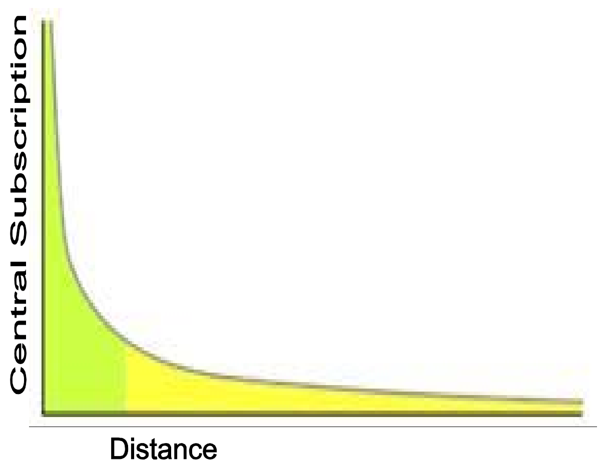
$$Energy\ consumed\ to\ receive\ a\ bit = \frac{50nj}{bit} \tag{4.2}$$

$$Transmit\ Energy = E_{amp} + d_{i,j}^2\ , \tag{4.3}$$

where d is the distance to transmit between sensors i to sensor j, from this we get the Power rule based on the distance d of nearest sensor to the farthest away sensor, substituting in the above equation (4.1) and summing up the total energy required for all transmissions within one meter, two meters, three meters, four meters and extending up to $(d-1)$ meters to a progressive sequence in equation (4.5) (as shown in Fig. 3(a).



(a)



(b)

Fig. 3. (a) Shows fixed energy overhead with distance in transmission, (b) Plot of the theoretical expected lifetime using Power Law [16], being used to demonstrate ranking of popularity. To the right is the long tail, to the left are the few that dominate (also known as the 80-20 rule).

To sum up the total energy consumption we can write it in the form of Power Law [16]:

$$Power\ Law = f(x) = ax^2 + [\![o(x]\!]^2) \tag{4.4}$$

Substituting d-distance for x and k number of bits transmitted we equate as.

$$f(d) = kd^2 + [\![o(d]\!]^2) \tag{4.5}$$

Taking Log both sides,

$$log(f(d)) = 2\ log d + \log k \tag{4.6}$$

Notice that the expression in equation (4.6) has the form of a linear relationship with slope k, and scaling the argument induces a linear shift of the function, and leaves both the form and slope k unchanged. Plotting to the log scale as shown in Fig. 3(b) we get a long tail showing a few nodes dominate the transmission power compared to the majority, similar to the Wikipedia reference 80-20 rule of Power Law [10].

4.3. Scale Invariance Property in Clustering for Energy Dissipation in RF Based Applications

As novel sensor applications are deployed to provide reliable data over the life-time [10] of the sensor network, with current routing algorithms [7] which are dependent to communicate with a central coordinator the instantaneous drain on the sensors are very demanding. As shown in the previous equation (4.6) in logarithmic scale for point to point transmission, we can extend this by clustering C nodes in the same range as shown in equation (4.8).

$$f(d) = kd^2 + [\![o(d]\!]^2) \tag{4.7}$$

$$[\![f(cd) = k(cd]\!]^2) = c^k f(d) \propto f(d) \tag{4.8}$$

From the equation (4.8) we can infer that the property is scale invariant even with clustering c nodes in a given radius k. This is validated from the simulation results [8] obtained latter in the result section, which show optimal results (minimum loading per node) [8] when clustering is $\leq$ 20 % as expected in theory (80-20 rule) from Fig 3(b). It is true, however, that the sensor measurements in the operation region are spatially correlated, to be efficient in a large sensor network partitioning the network into special clusters in done periodically and data needs to be aggregated locally by fusing all sensor reading at the cluster head. This data is periodically routed to a central coordinator which is a collaborative effort of all the active nodes in the sensor network.

4.4. Fault Rate

Large deployment of sensor network that use an efficient distributed algorithm to select cluster heads every round, due to rotating of cluster heads the network lifetime [10] is extended without faults. The fault rate of such an algorithm can be defined as the residual percentage (rei) [4] of good sensor when the network incurs faults due to resource drain. This is typically referred to as the sensor networks residual energy; if the fault rate is higher the cluster head selection algorithm is less optimal. The two dimensional simulation model is expressed for distributed and passive cluster based routing. In the paper the fault rate is measured for both the cases for algorithm complexity, multi-hop dependency, MAC layer losses and Bit error rates. The expected fault rate with respect to Bayesian normalized probability is shown in Fig. 5.

We will say that we are trying to find the optimal distributed threshold to select cluster heads c , out of all possible routing algorithms, that maximizes the probability of c , Cluster head selection with least percentage of good remaining sensors. Number of faults given the original measurement M:

$$P_{max} = \frac{\textbf{Clustering Algorithm}}{\textbf{Residual energy of the network at the Lifetime calculation}} \tag{4.9}$$

By Bayes theorem this is equivalent to

$$P_{max} = \frac{\textbf{Residual energy of the network at Sim 1, Sim2, Sim3 calculationClustering Algorithm}}{\textbf{Clustering Algorithm}} \times P_{CH} \tag{4.10}$$

4.5. Bayesian Classifier

Sensor networks are deployed in a dense configuration due to its limited radio range and fixed non renewable energy resources due to computational/networking characteristics of sensor networks. To collaboratively use the limited resources distributed algorithms, select a single node which transmits serially using its UART pre-processed sensed data information using many local resources. As the cost of radio transmission is much more than local sensing, the sensor network uses two different topologies to address the energy cost at the cross-layer stack. The network layers uses the upper layers assuming MAC layer abstraction to optimally pick cluster heads by using a fixed probability density function (pdf) of a network resource at the node, such as, remaining battery energy. This type of pdf is power-aware as it uses a collaborative function to minimize over use of network resources thus avoiding pre-mature node failures.

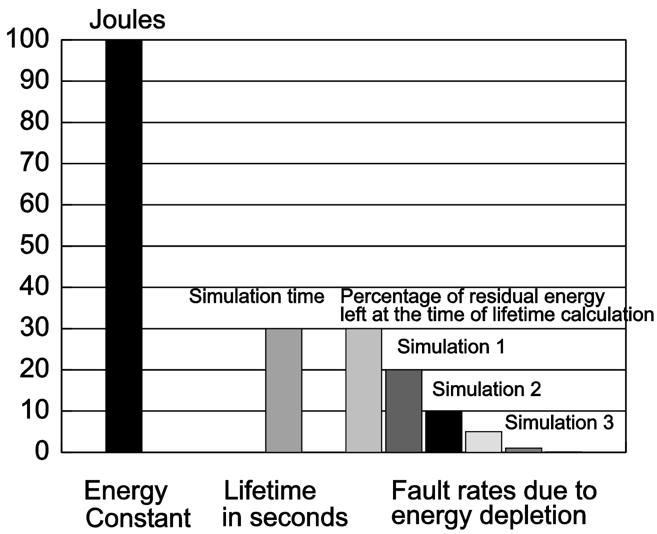
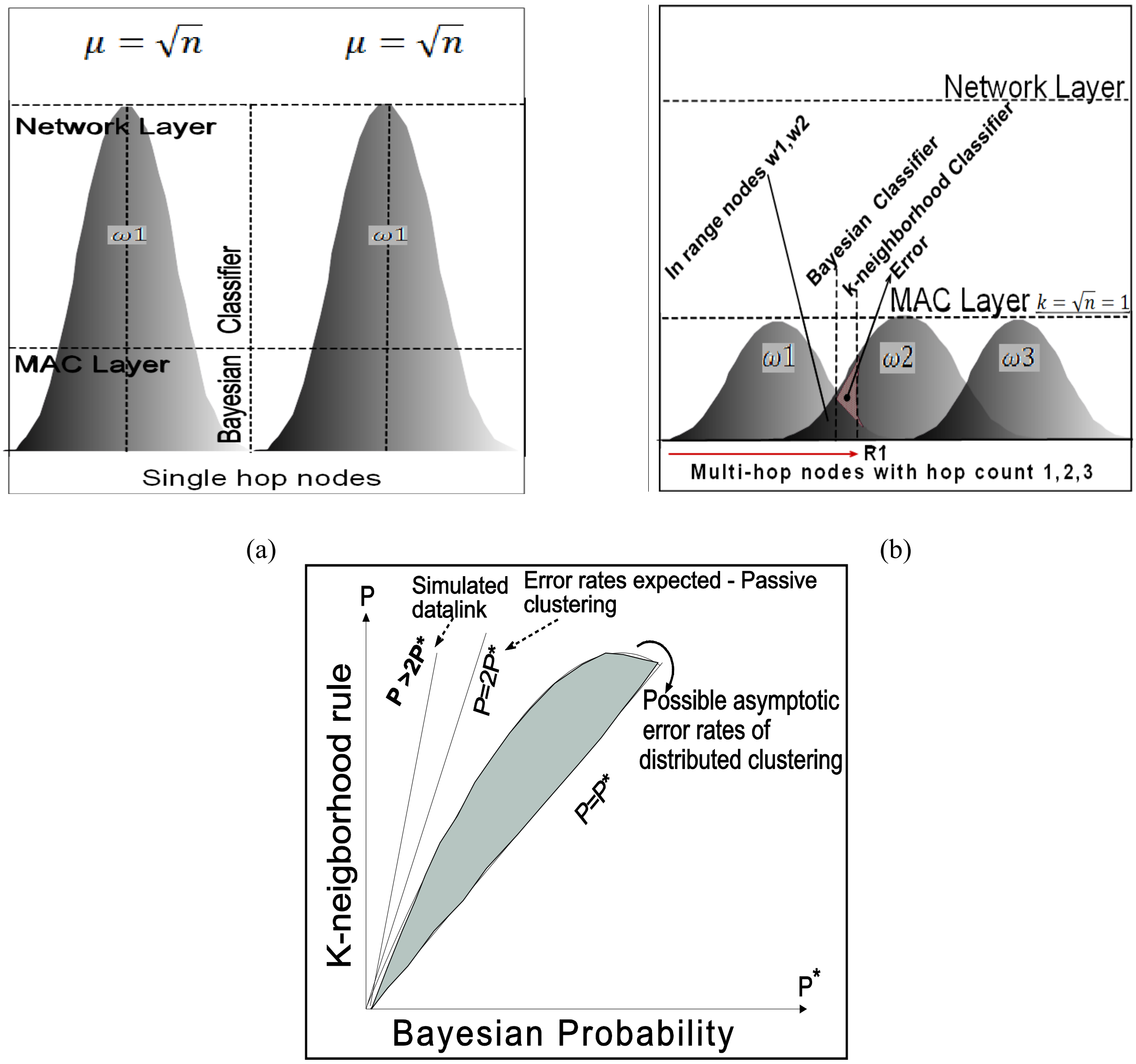


Fig. 4. Measurement metrics for node failures.

The MAC layer uses a k-neighborhood distance algorithm to find other nodes within its own limited range and uses a multi-hop schedule to the specific data transmitting node. This scheduling allows multi-hop nodes to use sleep cycles and lower their energy consumption while idling. These multi-hop algorithms use low-power listening and use a preamble to wake up nodes, sleep cycles when the transmitter is completely off and traffic based preamble to synchronize nodes to receive the data payload.

If Θ_1, Θ_2, Θ_3 are the data values of a parameter such as residual energy, observed values by the sensors, as large scale sensor deployment are a dense deployment as the reading are correlated only an average Θ_1 needs to be transmitted. As the clustering is based on the network layer which optimizes on radio range and not the sensing region it always is approximated and corrected using some training samples using less number of bits to be transmitted, this is the fundamental design based on power-aware data model.



(c)

Fig. 5. (a) Persistence clustering when CH probabilities are known a priori (b) Passive clustering when CH probabilities are unknown (c) Error Bounds of persistence & passive clustering Estimation of CH selection error and MAC layer routing using Bayesian distributed rule.

4.6. Lifetime Calculation

To understand this the layer III MAC duty cycle we use a micro kernel real-time clock which allows to measure different states of the MAC. It can be conveniently divided into T_x, R_x, Idle times for a given nodes lifetime. The duty-cycling can be defines as

$$Lifetime = \frac{(C_{batt} \times V \times 60 \times 60)}{(EnergyTx + Rx + Idle + Lis)} \times duty\ cycle \tag{4.11}$$

$$Amortized\ dissipation = \frac{(EnergyTx + Rx + Idle)}{3} \tag{4.12}$$

$$Lifetime = \frac{2000\ mAh}{Amortized\ dissipation\ mAh} \tag{4.13}$$

$$Lifetime = \textbf{Useful time in days(predicted for a AA battery)} \tag{4.14}$$

$$Lifetime = Actual\ simulation\ for\ algorithms\ used\ 3000\ joules\ as\ a\ measure \tag{4.15}$$

Substituting this amortized dissipation value for a standard battery of 2000 mAh into the lifetime equation with 0.01 % duty cycle a 100 ms preamble MAC.

4.7. Compression Rate

It is well known that the Huffman algorithm [19] and definition from table 1 finds a code minimizing average redundancy; this is so well known that the problem itself is often referred to as the “Huffman problem.” The Huffman algorithm is a greedy algorithm built on the observation that the two least likely items will have the same length and can thus be considered siblings in the coding tree. A reduction can thus be made in which the two items of weights $w(i)$ and $w(j)$ can be considered as one with combined weight $w(i) + w(j)$, and the codeword of the combined item determines all but the last bit of each of the items combined, which are differentiated by this last bit. This reduction continues until there is one item left, and, assigning this item the null string, a code is defined for all input items. In the corresponding optimal code tree, the i^{th} leaf corresponds to the codeword of the i^{th} input item, and thus has weight $w(i)$, whereas the weight of parent nodes are determined by the combined weight of the corresponding merged item. Van Leeuwen gave an implementation of the Huffman algorithm that can be accomplished in linear time given sorted probabilities [20]. Shannon [21] had previously shown that an optimal l^{opt} must satisfy.

$$H(p) \leq \sum_{i \in \chi} p(i) l^{opt}(i) < H(p) + 1 \tag{4.16}$$

or equivalently,

$$0 \leq \bar{R}(l^{opt}, p) < 1 \tag{4.17}$$

Less well known is that simple changes to the Huffman algorithm solve several related coding problems which optimize for different objectives, shown to satisfy redundancy bounds of the form

$$\tilde{H}(p) \leq \tilde{L}(p, l^{opt}) < \tilde{H}(p) + 1 \tag{4.18}$$

$$0 \leq \tilde{R}(l^{opt}, p) < 1 \tag{4.19}$$

for some entropy measure $\tilde{H}$, cost measure $\tilde{L}$, and redundancy measure $\tilde{R}$. These bounds are the first of their kind for nontraditional Huffman codes, bounds which are functions of both entropy and $p(1)$, as in the traditional case [22]–[26]. However, they are not the first improved bounds for such codes; more sophisticated bounds on the optimal solution for one of these problems were given by Slepian & Wolf for correlated sources.

Table 1. Summary of Notations for Analysis of Huffman Coding.

Symbols	Definitions
$H(p)$	Normal entropy
$\breve{H}(p)$	Correlated/Minimized entropy based on *pmf* mass function
$\bar{R}$	Correlated redundancy measure
$\bar{L}$	Transmission cost measure in bits
l^{opt}	Optimal Huffman code length
$P(1)$	Huffman tree using *pdf* distribution

4.7.1. Slepian & Wolf Theorem

The Slepian-Wolf rate [13] region for two arbitrarily correlated sources x and y is bounded by the following inequalities, this theorem can be adapted using equation (4.20)

$$R_x \geq H\left(\frac{x}{y}\right), R_y \geq H\left(\frac{y}{x}\right) \text{ and } R_x + R_y \geq H(x, y) \tag{4.20}$$

If the correlated sources are differing by a few bits, the possible number of codewords can be represented as 2^m, where m= no. faulty bits [5]. In our case $m = 2$ as the parameters are distributed whilst collected locally at the cluster head.

4.7.2. Distributed Source Coding with Side Information

In sensors networks several measured values are sensed in a distributed manner and these are aggregated according to the users query. The goal of all the encoder is analogous to the previous section where it uses cosets. Table 2 illustrates the bin formation to reduce the overall bits needed for transmission. Considering the case of distributed sensing application, the encoder is further designed with a machine learnable redundancy range which is specific to each and every application. This mutually redundant measured range is correlated with sensors which are in the same wireless range and connected to a parent. This information, also called side information is shared with the decoder. Owing to side information, even lesser number of bits is needed to represent the changing values coming from each cluster heads transmitting to the joint decoder. Encoder and decoder have access to the side information Y. which is correlated to X and can be represented by the equation (4.20). According to the Slepian-Wolf Theorem [13], established in 1971, that the number of bits needed by using the theorem is lesser, than the total entropy for both the two arbitrarily correlated sources $H(x), H(y)$.

Table 2. Bit reduction in terms of correlated sources.

$$\begin{vmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \end{vmatrix} = 00 \quad \begin{vmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{vmatrix} = 10 \quad \begin{vmatrix} 0 & 0 & 1 \\ 1 & 1 & 0 \end{vmatrix} = 01 \quad \begin{vmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \end{vmatrix} = 11$$

4.7.3. Probability Mass Function

In probability theory, a probability mass function (abbreviated *pmf*) is a function that gives the probability that a discrete random variable is exactly equal to some value(which occurs in a given static region of high density or a two dimensional model such as planar graphs). A *pmf* differs from a probability density function (abbreviated *pdf*) in that the values of a pdf, defined only for continuous random variables, are not probabilities as such. Instead, the integral of a pdf over a range of possible values (a, b] gives the probability of the random variable falling within that range. As an example, if every node has its residual value as *rei* index [4] then if a given node needs to optimally do a communication task. Then it needs to find only the total energy it needs from its neighbors *rei* index's which adds up to a total cost of 1. This is typically a local cumulative algorithm as it terminates in $O(1)$ operation.

4.7.4. Probability Density Function

In probability theory, a probability density function (abbreviated *pdf*), or density, of a random variable is a function which describes the density of probability at each point in the sample space (mostly drawn with an overall global distribution). The probability of a random variable falling within a given set is given by the integral of its density over the set. As an example, if every node has its residual value as *rei* index then if a given algorithm needs to find active cluster heads then it looks for highest or better *rei* index from all the available active nodes to assign cluster heads. This is typically a distributed global cumulative scale algorithm as it terminates in $O(n)$ operations.

5. Cross-Layer Error Analysis - Algorithms

5.1. Estimate of the Active CH Value for Known Densities

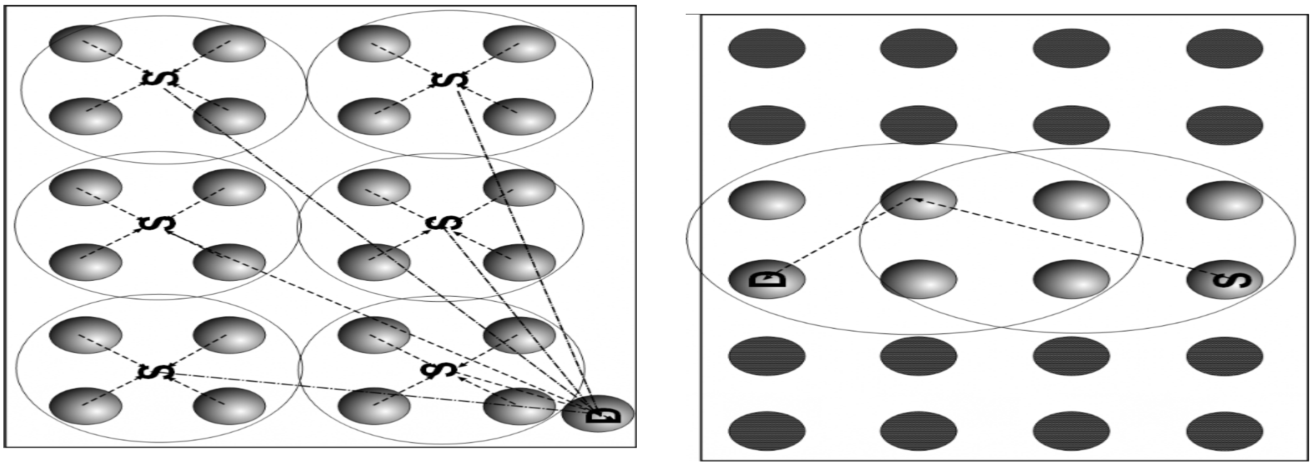
The simulated routing algorithms such LEACH-S [12], LEACH-E [8] and CRF [8] as described in the above table 2 use the knowledge that the nodes which are sensing are correlated and have known densities such as cluster size and radio range. The underlying model uses different ways to select the cluster heads to minimize the error rate by using a *pdf*. When the sensor faults happen due to fixed energy resources at the cluster head the total energy unused at the end of its lifetime is the residual rate [6], the routing algorithms tries to minimize this error criterion. As this model uses the network layer and the only dependant variable is the fixed lifetime model [10]. The complexity of the algorithm can be defined by using the standard implementation of the LEACH distributed algorithm and its power-aware variations.

$$Og(x) = f(x): 0 \leq f(x) \leq cg(x) \tag{5.1}$$

$$\Omega g(x) = f(x): 0 \leq cg(x) \leq f(x) \tag{5.2}$$

$$\Theta g(x) = f(x): 0 \leq c_1 g(x) \leq f(x) \leq c_2 g(x) \tag{5.3}$$

Complexity of the routing algorithms for LEACH is shown in equation (5.1), LEACH-E equation (5.2) and CRF equation (5.3). In the next section we will use only the lower layer such as power-ware MAC and estimate the multi-hop routing errors. In this case the model is not dependant on the fixed energy resources and only dependant on k-nearest neighbor rule (or having sufficient nodes distributed in a Poisson distribution) it uses to find its multi-hop nodes as shown in Fig. 6(b). As the node probability are not known a priori the error rates are much higher than the persistence clustering.



(a) (b)

Fig. 6. (a) LEACH single-hop nodes, (b) Passive clustering algorithms with multi-hop nodes.

6. Simulation

6.1. Results from the Network Layer

Simulation models large number of nodes and calculates the lifetime when sensor faults are more likely to happen, the Table 3 shows number of cluster heads and the fault rate for distributed clustering and passive clustering [3]. Simulation results confirm as shown in Fig. 7, the fault rate is network size invariant and converges to the optimal values derived in theorem 1 and 2 [3].

Table 3. Summary of notations for analysis of Bayesian classifier.

Symbols	Definitions
N	Total number of deployed nodes
N	Number of nodes in the cluster
μ	Density of the class
P_{MAX}	Bayesian class rule
$R_{x,} R_{y}$	Entropy of correlated sources
R, r	Radio range
P	K-neighborhood fault probability
P^{*}	Bayesian probability
Ω	Bayesian classes
S	Data source node
D	Destination node
Θ	Nodes residual densities
CH	Cluster head
$P(\omega_i\|\|x)$	Conditional probability
$P(x\|\|\omega_i)$	Class conditional probability

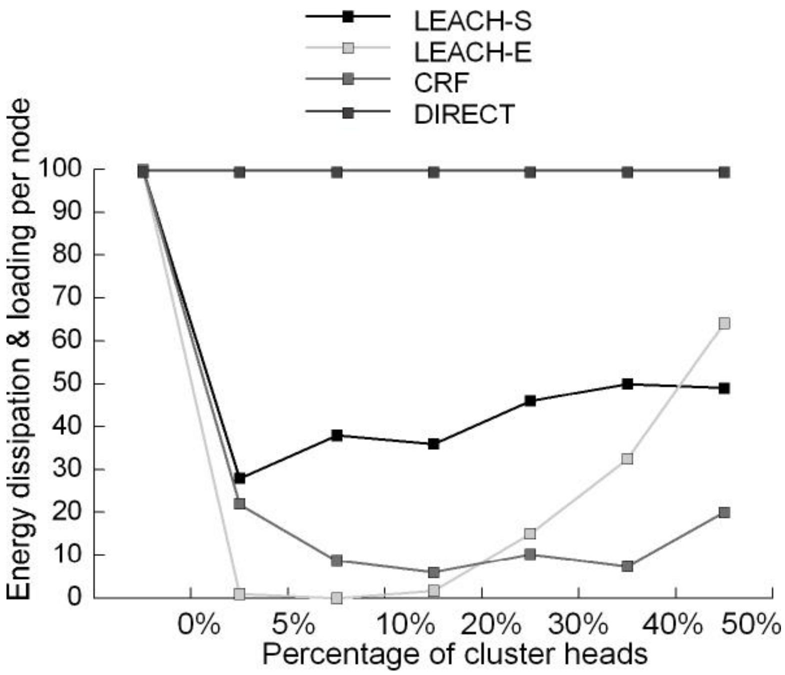


Fig. 7. Show energy dissipation node loading (with link layer abstraction).

7. Lifetime Cross-Layer Error Analysis - Routing Protocols

7.1. Results from the MAC Layer

When node densities are not known in advance due to asynchronous operation and unscheduled sleep schedules polling and other characteristics of sensor due to its dependence in fixed resources. The problem due to this is for data transmitting nodes needs to find a near neighbor in a deterministic way by which it can build a passive cluster to multi-hop its data. This uses minimal clustering overhead as it does not use the upper layers during communication synchronization. The behavior of the k-Nearest-Neighbor rule [3] will be directed by in our simulation a two-dimensional node distribution of $n \geq 100$ where node density has one or less neighbors. The unconditional average probability of error occurring will be found over all nodes positioned at coordinates specified by x :

$$P^*(e) = \int P(e|x)p(x)dx \tag{7.1}$$

The convergence of the nearest neighbor for distributed clustering and passive clustering are derived, the distributed clustering case is

$$P = P^* \tag{7.2}$$

For passive clustering is given by

$$P = 2P^* \tag{7.3}$$

As shown in simulations [6] where lower bound for LEACH-S when it becomes faulty and the remaining residual energy using the cross-layer simulator is $P(e) = 0.27\%$ which is the fault rate. In the case of passive clustering when node density $p = 0.1$ or using the k-neighborhood rule [3] the node densities are unknown in this case due to high likely-hood of faults. The protocol simulation results [3] that the upper bound has error rate of $P(e) = 0.41\%$ which converges to the proof derived in theorem 3 and theorem 4 [3] and the upper bound.

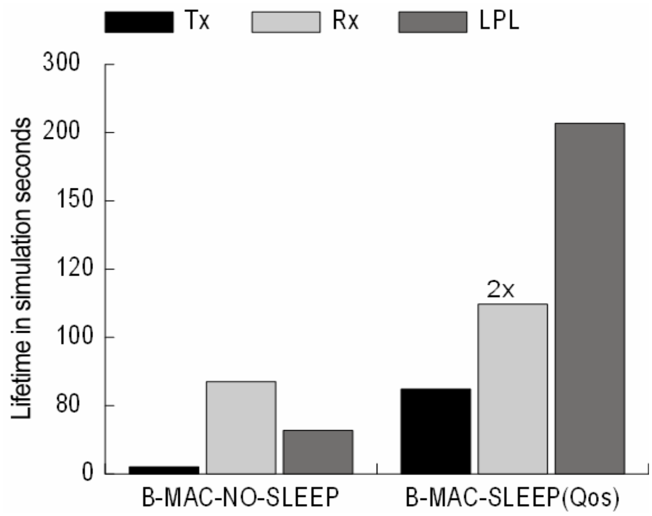


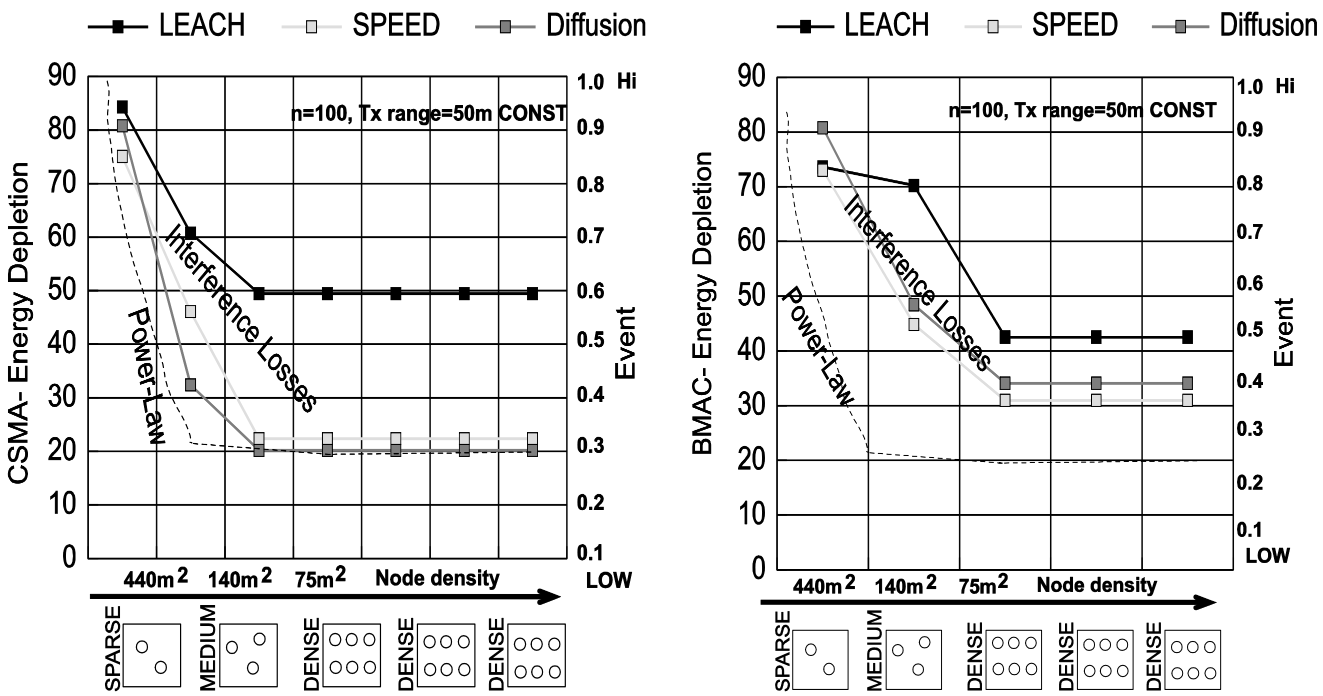
Fig. 8. Shows the lifetime of the overall sensor network increases when routing algorithm uses sleep scheduling by 2 xs.

This work used the existing simulation models that are network-based, and specified the Qos framework for data reliability needed for sensor networks. The fusion of energy harvesting applications with power-aware MAC was studied in terms of deployment of low-level protocols for 802.11, CSMA, and B-MAC. Furthermore, if the data is routed using multi-hop algorithms and is MAC-centric, then the distributed sleep scheduling [2] is observed to reduce the percentage of energy lost during overhearing and collision as shown in Fig. 8. The performance of routing algorithms with MAC losses has a long tail which is similarly observed in Power Law. Lastly, the asymptotic lower and upper bound for data-link reliability has been theoretically predicted using Bayes probability. Simulation results show that the probability of data-link reliability is greater for clustering algorithms due to conditioning at the cluster head in CSMA which helps sensor network protocols and more energy efficient when using B-MAC. A FARM which uses a low-duty cycling MAC and renewable energy harvesting built-in part of the routing protocol performs well in a dense sensor network configuration and has the added advantage of longer lifetime with Qos close to regular sensor network algorithms.

8. Cross-Layer Data-Link Error Analysis - MAC Aggregation Protocols

8.1. Results from the MAC Layer Using a Propagation Model

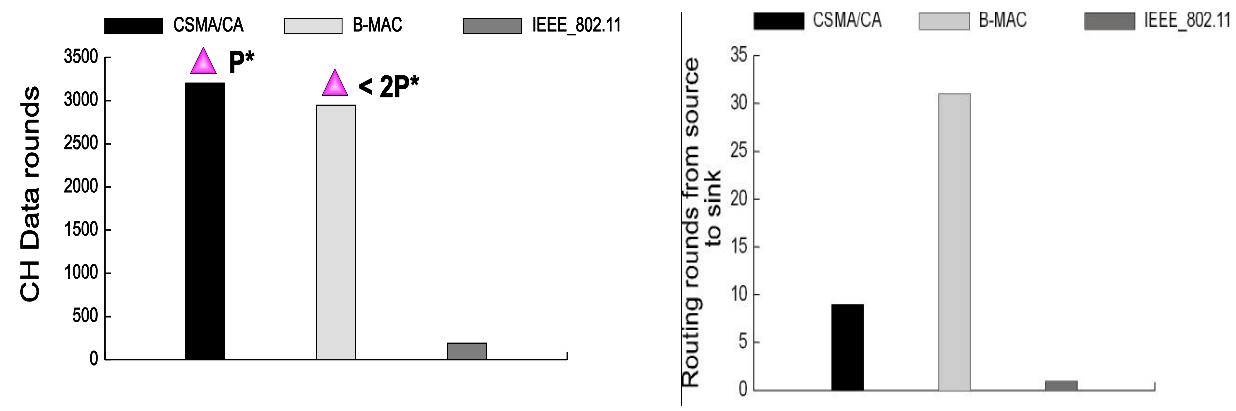
In the previous case MAC abstraction is used which does not take into account the propagation losses and protocol retries at the MAC level. To simulate the wireless channel we use GlomoSIM [17] bit error ratio (BER) simulator and implement the routing algorithms for multi-hop cases. The routing algorithm implemented is SPEED which is a geographic routing algorithm which uses two dimensional coordinate spaces to calculate the path from the node coordinates. Many runs into the protocol simulation suggest that the radio characterization for CSMA Fig. 9(a) and B-MAC is comparable, Fig. 9(b) when the node densities are known.



(a) (b)

Fig. 9. MAC performance comparison: (a) CSMA-MAC, (b) B-MAC.

The radio characterization for CSMA [1] is prone to faults when compared to B-MAC, when using in multi-hop modes where the node densities are unknown. The protocol performance results show that the data packets received during useful lifetime is $3X$ times better Fig. 10(b) in B-MAC when compared to CSMA and error rates are $\geq 2P^*$ higher than the theoretical Bayesian limit [4] of $P = 2P^*$ as derived in theorem 3 and theorem 4 [4].



(a) (b)

Fig. 10. Data aggregation SPEED /Diffusion/LEACH:
(a) Local data aggregation, (b) Multi-hop protocols to sink.

8.2. Bit Error Ratio (BER)

The BER is dependent on the packet size and the frequency of the radio. As these increases with distance and multi-hop routing algorithms with no Qos support, we try to address this in terms of the actual payloads which are typically sensed values. As the BER rate is constant for a given channel we try to reduce the data error rate by further reducing numbers of bits needed to transmit by finding values which differ by only 1-bit. This is accomplished by using a $\tilde{H}(p)$, *pmf* with a geometrical cluster for a fixed radio range. This technique further sorts on lower values to minimize any potential error which can trigger a false high alarm.

8.3. Addressing High Bit Error Ratio (BER) and Noisy Channels

8.3.1. Frequency Dependency

For short distances,

$$d = \frac{\text{Distance between the communicating Sensor Nodes}}{\text{Speed of Light}} \tag{8.1}$$

$$\mathrm{Pr}\square = \frac{(\mathrm{Pt} * \mathrm{Gt} * \mathrm{Gr} * \lambda^2)}{(4\pi)^2 * \mathrm{d}^2 * \mathrm{L}^2} \tag{8.2}$$

- Pt is the transmitted signal power
- Pr is the received signal power
- G_t , G_r are the antenna gains of the transmitter and the receiver respectively.
- L is the system loss, and λ is the wavelength.

For longer distances using, Two-ray ground reflection model

$$\mathrm{Pr}\square = \frac{(P_t * G_t * G_r * h_t{}^2 * h_r{}^2)}{(d^4 * L)} \tag{8.3}$$

h_t and h_r - heights of transmit and receive antennas respectively and d is the distance. The above equation (8.3) shows a faster power loss than for Free Space Model as distance increases. The other observation is it is independent of frequency for longer distances, so a higher such ad 2.4 GHz compared to 900 MHz will be able to reduce the BER.

Thus, a distribution has a min-entropy of at least *b* bits if no possible state has a probability greater than 2^{-b}. Here we use a 3-bit prefix code, this code will be.

8.3.2. Resilient Error Correction by Code Design

An application for this decaying exponential variant was given in [21]; in this application, a communication channel has a window of opportunity with a total duration (in bits) distributed geometrically with parameter a, Fig. 1,11. The probability of successful transmission is given probability mass function p and 0 < a < 1, find a code minimizing

$$L_a(p, l) \triangleq \log_q \sum_{i \in \chi} p(i) a^{l(i)} \tag{8.4}$$

$$P_{Success} = a^{L_a(p,l)} \tag{8.5}$$

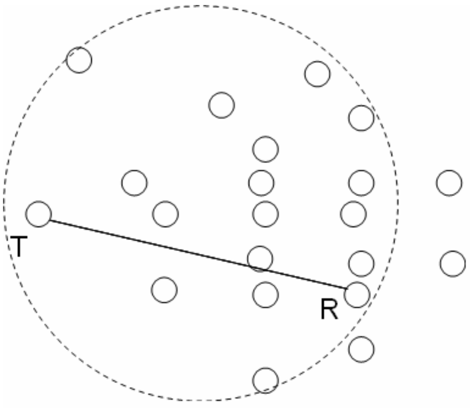


Fig. 11. Wireless channel simulation for a given geometrical area from transmitter (T) to a receiver (R).

In 2004, Drmota and Szpankowski [27] proposed a problem which, instead of minimizing average redundancy,

$$\bar{R}(l,p) \triangleq \sum_{i \in X} p(l(i) + \log[p(i)])$$

minimizes maximum pointwise redundancy

$$R^*(l,p) \triangleq max_{i \in X}(l(i) + \log[p(i)]) \text{ ,} \tag{8.6}$$

This was later noted to be solvable via a variation of Huffman coding [28] derived from that in [29], one for which

$$f(w(i), w(j)) = 2\max(w(i), w(j)) \tag{8.7}$$

A few observations can be used to find a series of improved lower and upper bounds on optimum maximum pointwise redundancy based on

i. In a Huffman-like tree for a maximum pointwise redundancy code, the weight of the root w_{root} determines the maximum pointwise redundancy, $R^*(l,p) = \log w_{root}$.
ii. The total probability of any subtree is no greater than the weight of the subtree. This can be inductively observed.
iii. In the Huffman-like coding, items are merged by non decreasing weight. This can be observed by noting that any new merged item has weight greater than either of its merged items. In fact, any new merged item has weight at least twice as great as either of the merged items, due to equation (8.7).

A fourth observation is in the form of the following lemma:

Lemma 1: Given a probability mass function p for $n = |X|$ items, if $p(1) \leq 2p(n-1)$, then a minimum maximum pointwise redundancy code can be represented by a complete tree, that is, a tree such that

$$\sum_{i \in \chi} 2^{-l(i)} = 1 \quad \text{and } |l(i) - l(j)| \leq 1 \text{ for all } i,j \in \chi .$$

Proof: A code with minimum maximum pointwise redundancy is always obtained when using a Huffman style algorithm combining the items with the smallest weights, w' and w'', yielding a new item of weight $w = 2max(w', w'')$, and this process being repeated on the new set of weights, the tree thus being constructed up from the leaves to the root. Since a tree always satisfies that

$$\sum_{i \in \chi} 2^{-l(i)} = 1 .$$

Consider the tree formed by the application of this algorithm. Since the first (and thus least weighted) combined item is of weight $2p(n - 1)$ as shown in Fig. 12, clearly no combined item need be merged with another item until the point at which item 1 is merged or thereafter. The algorithm can, in this case, be seen as pairing off items in the order of a queue sorted from least weighted to most weighted and placing the paired-off items in the rear of the queue. Because items are processed with increasing weight, this processing occurs in queue order, and thus, at any given point, every item is processed about the same number of times as any other; the difference can only be one. This is true when the algorithm terminates and codeword length is equal to the number of times an item is (by itself or as part of a combined item) processed. Thus $|l(i) - l(j)| \leq 1$ for $all\ i,j \in X$, and the complete code tree is optimal. We can now present the improved redundancy bounds in Fig. 13(a, b) and Fig. 14.

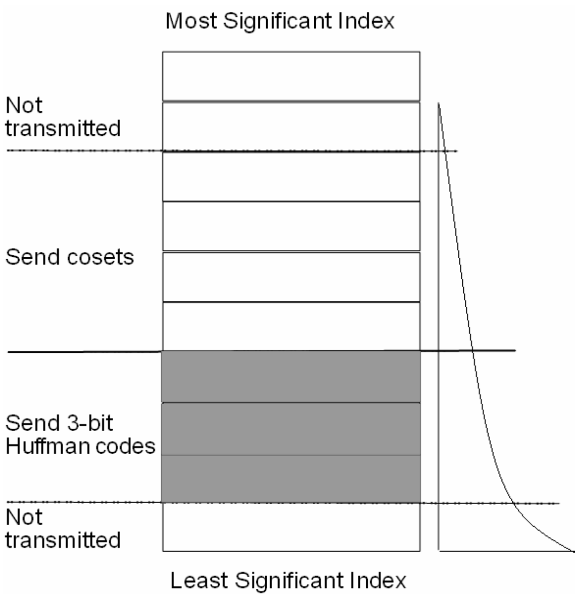
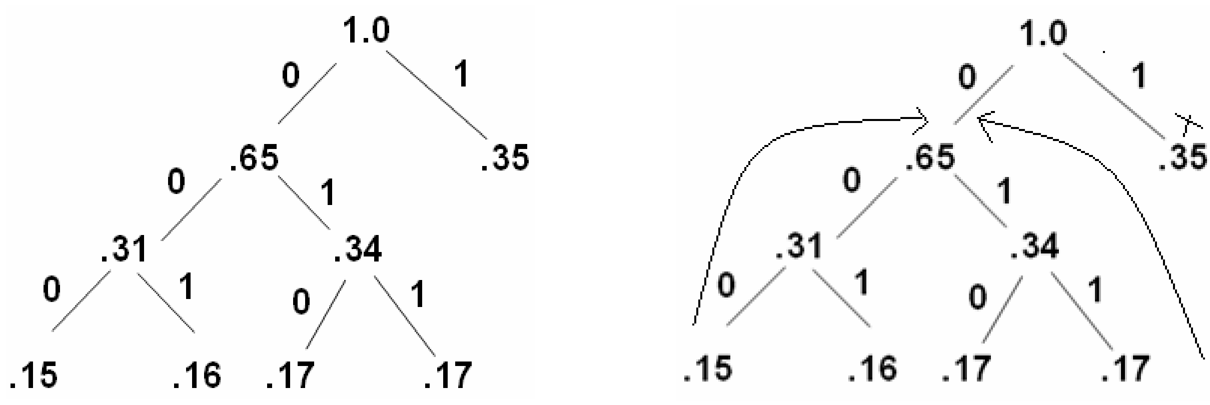


Fig. 12. Weights on the encoded bits transmitted for sensed data.



(a) (b)

Fig. 13. (a) Shows when MSB is not correlated (b) Shows LSB are different by one bit after using minimal entropy. Designing codewords with $|l(i) - l(j)| \leq 1$, using lower bound entropy.

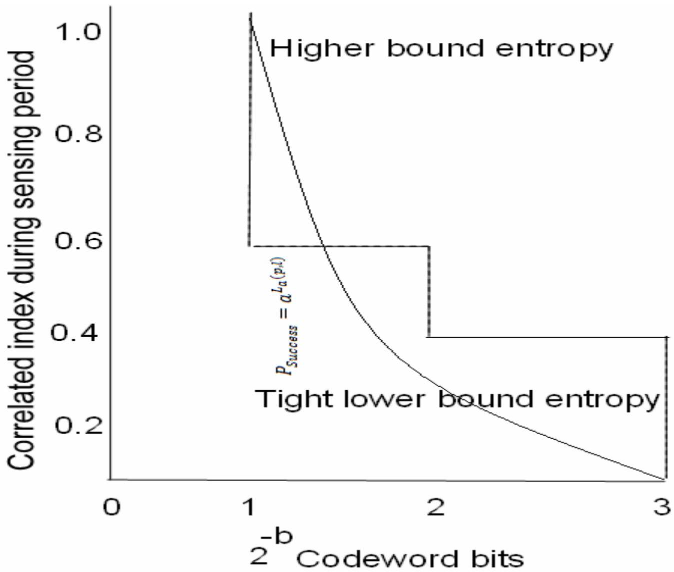


Fig. 14. Sensor data fault-redundancy.

9. Cross-Layer Lifetime Analysis - MAC Integration

9.1. Lifetime Modeling

To calculate node duty cycle and lifetime, we develop an arrangement of virtual clusters which streams data to the base station. Table 4 lists the primitive operations performed by MAC states which are extended for power-aware for normal traffic. The virtual clustering protocol implement a minimal version of LEACH which allows select cluster heads periodically and rotate them in a distributed way. Data aggregation is done from all the nodes part of the virtual clusters during the current time slot. We simulate a low data date application which samples every 10 seconds and passed the data to a base station. The MAC integration uses CSMA/BMAC/TDMA for testing the sample application with periodic traffic. As CSMA does not have any power saving scheme it does not perform well, on the other hand B-MAC has low power listening (LPL) which allows cutting down on idle listening. Here we introduce a basic protocol which is specific to TDMA based frame.

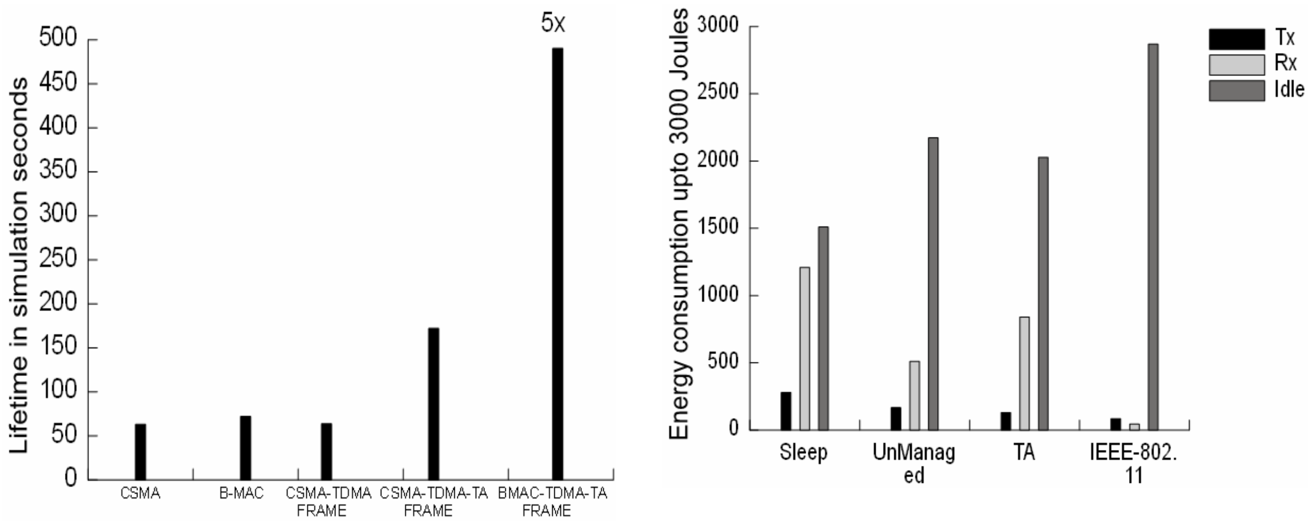
A node will keep listening and potentially transmitting as long as it is in active period. An active period ends when no activation event has occurred for a time *TA*. An activation event is:

- The firing of a periodic timer
- End-of transmission of a node's own data packed or acknowledgement

A node will sleep if it is not in an active period. Consequently, TA determines the minimal amount of idle listening per frame. Due to better synchronization of the TDMA frame based MAC, the idle listening is cut down when TA period is reached. Results from simulation of 100 nodes with virtual clustering shows that TDMA-TA based power optimization using B-MAC at the MAC layer does 5x times better as shown in Fig. 15(b) to enhance the lifetime of the sensor network.

Table 4. Summary of notations for analysis of MAC performance.

Symbols	Definitions
C_{sleep}	Sleep Current
Tx	Transmit energy consumed during its lifetime
Rx	Receive energy consumed during its lifetime
Idle	Idle energy consumed during its lifetime
$TDMA_{no-duty-cycle}$	When using virtual clustering of nodes n, the node is awake for the complete time-slot.
$TDMA_{TA}$	When using virtual clustering of nodes n, the node is put to sleep immediately after the protocol completes for the current time-slot.
C_{batt}	Capacity of battery
V	Voltage
$L_{preamble}$	Preamble Length (bytes)
L_{packet}	Packet Length (bytes)
t_i	Radio Sampling Interval (s)
n	Neighborhood Size (node $\leq$ 20%)
r	Sample Rate (packet/s)
t_l	Expected Lifetime (s)



(a) (b)

Fig. 15. MAC performance in lifetime seconds: (a) CSMA, B-MAC with LPL and CSMA-TDMA Frame (b) CSMA-TA Frame, B-MAC-TDMA-TA Frame.

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