Distributed Source Coding for Sensor Data Model and Estimation of Cluster Head Errors using Bayesian and K-Near Neighborhood Classifiers in Deployment of Dense Wireless Sensor Networks

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***Abstract*—The lifetime calculation of large dense sensor networks with fixed energy resources and the remaining residual energy have shown that for a constant energy resource in a sensor network the fault rate at the cluster head is network size invariant when using the network layer with no MAC losses. Even after increasing the battery capacities in the nodes the total lifetime does not increase after a max limit of 8 times. As this is a serious limitation lots of research has been done at the MAC layer which allows to adapt to the specific connectivity, traffic and channel polling needs for sensor networks. There have been lots of MAC protocols which allow to control the channel polling of new radios which are available to sensor nodes to communicate. This further reduces the communication overhead by idling and sleep scheduling thus extending the lifetime of the monitoring application. We address the two issues which effects the distributed characteristics and performance of connected MAC nodes. (1) To determine the theoretical minimum rate based on joint coding for a correlated data source at the single-hop, (2a) to estimate cluster head errors using Bayesian rule for routing using persistence clustering when node densities are the same and stored using prior probability at the network layer, (2b) to estimate the upper bound of routing errors when using passive clustering were the node densities at the multi-hop MACS are unknown and not stored at the multi-hop nodes a priori. In this paper we evaluate many MAC based sensor network protocols and study the effects on sensor network lifetime. A renewable energy MAC routing protocol is designed when the probabilities of active nodes are not known a priori. From theoretical derivations we show that for a Bayesian rule with known class densities of ω_1, ω_2 with expected error P^* is bounded by max error rate of $P = 2P^*$ for single-hop. We study the effects of energy losses using cross-layer simulation of large sensor network MACS setup, the error rate which effect finding sufficient node densities to have reliable multi-hop communications due to unknown node densities. The simulation results show that even though the lifetime is comparable the expected Bayesian posterior probability error bound is close or higher than $P \geq 2P^*$.**

***Index Terms*—Sensor Data Reliability, Baysian Error Classifiers, Slepian & Wolf Coding, Cosets.**

I. Introduction

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.

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 $\theta_1, \theta_2, \theta_3$ 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. In the MAC layer which polls the channel to check for any activity while receiving and during transmitting to avoid collision and uses best effort QoS for the messages to be forwarded. The data sensing nodes are single hop while the forwarding nodes are multi-hop nodes. The data values which are forwarded are discrete and updated according to some trend in the data. Some measured values may be

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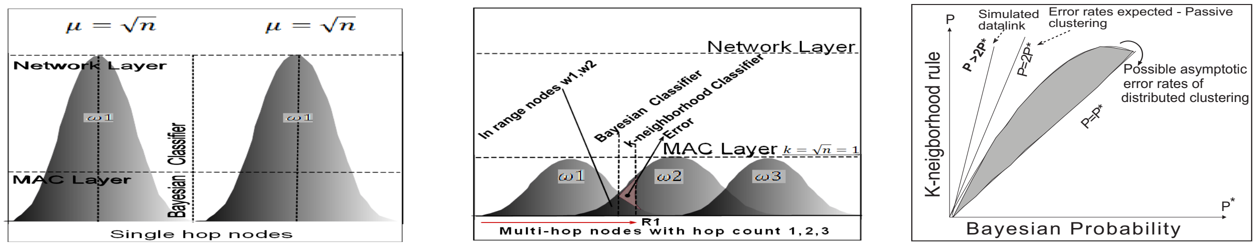


(a) Persistence clustering when CH probabilities are known a priori (b) Passive clustering when CH probabilities are unknown (c) Error Bounds of persistence & passive clustering

Fig. 1. Estimation of CH selection error and MAC layer routing using Bayesian distributed rule

changing more quickly than others creating different traffic patterns that are data driven. The multi-hop nodes do not have any sensors and act like routers which uses best effort QoS and constantly adapts its polling depending on the data trend, this is fundamental to the design of polling the channel which uses on-demand traffic predictions. Model implementation assumes $\theta_1, \theta_2, \theta_3$ are always transmitted when changes happen and typically it is re-transmitted at a constant rate of 10 minute intervals keeping the channel polling of a set of nodes to guarantee the QoS.

Figures 1(a,b) illustrates the Bayesian classifier for pdf based clustering and multi-hop based passive clustering. For the theoretical and mathematical proofs please refer to chapter 2,4 in the mentioned reference [6]. This paper builds from previous work [2] and extends the two dimensional Bayesian model [6] to optimize on power-aware routing algorithms in representing sensor network. The routing algorithms are implemented at the network layer which have known density of nodes by using prior selection and at MAC layer which have unknown node densities due to limited transmission range. The Bayesian classifiers [6] which are specific to the routing topology uses features to maximize the lifetime of the sensor network and minimize on sensor faults. This Bayesian classifier helps in predicting the theoretical fault rate bounds by knowing the node densities validated also through real simulation. In section II, the sensor data model is described with respect to sampling and compression needs at the cluster heads. In section III, the Source coding rate is introduced for correlated sources using error corrected codes. In section IV, the scalability of the sensor network is modeled using Power Law and Bayseian Classifier and how it effects distributed clustering and passive clustering routing. In Section V, a distributed algorithm is simulated without MAC to find error bounds for a large-scale deployment. Section VI, uses cross-layer energy model with a standard simulator using crossbow mote energy model to analyze lifetime for various routing algorithms with MAC and data link losses. The summary of results take into consideration protocol performance for a fixed battery model and its implications to MACS which use renewable energies. The corresponding routing errors with same node densities are bounded by the theorems discussed in Fault rates, and summarized in a table(figure V).

II. Data Models

A. Probability model

Where d is the distance to transmit between sensors i to sensor j. We designed the compression algorithm for a large distributed sensor network with a desired channel rate, a fixed length code to represent real sensed values at the encoder using (c,k,d), Where c is the code, k is the length and d is the distance from the average P_{Max} cluster heads. This technique which allow using less number of bits to represent the newly encoded data is sent to the decoder by sharing the expected local value at both ends. As a rule, compression algorithms use a probability model based on the entropy of the source. Iyengar [2] defined a Bayesian fault-tolerant algorithm [2] in sensor network using an abstract sensor which can be *tamely faulty* and *widely faulty*. For larger sensor network deployment, this model helps predict the error bounds in terms of the varying sensing values. In this paper we adapt the Bayesian rule [6] to select cluster heads for known node density and extend it to find the upper bounds related to unknown densities for solving the optimal routing problem at the network layer in sensor networks. The latter is more relevant for renewable energy resources [3]. Where the number of active sensors connected to the network is not known, at any given time.

Entropy of general sensing source is a sequence of length n from the source and is given by

$$H(S) = \lim_{n \to \infty} \frac{1}{n} G_n, where \tag{2.1}$$

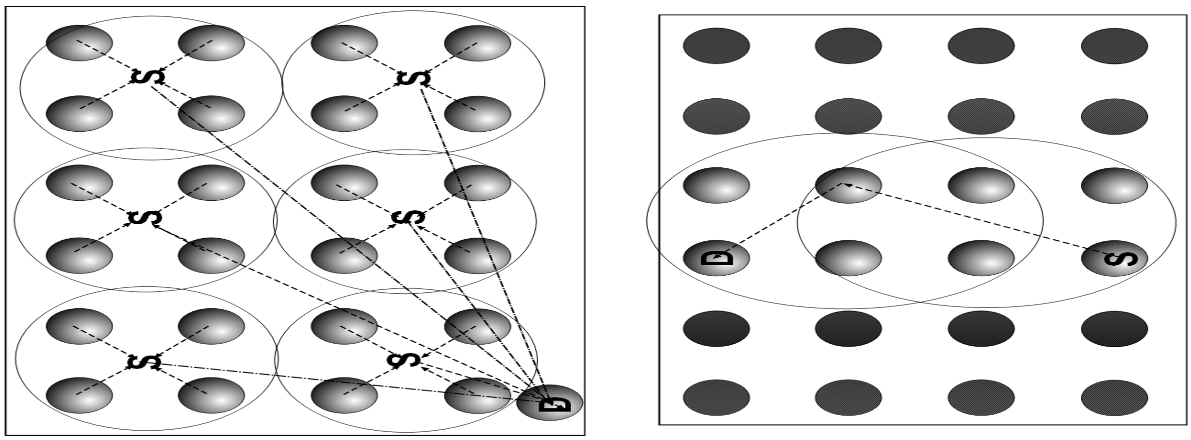
$$G_n = -\sum\sum ... \sum P(X_1 = i_1, X_2 = i_2 ... X_n = i_n) \\ \log P(X_1 = i_1, X_2 = i_2 ... X_n = i_n)$$

In sensors where each element in the sequence is independent and identically distributed (i.i.d.), with this statistical model, we can modify the entropy of the first order to equation (2.1)

$$H(S) = -\sum P(X_1) \log P(X_1) \tag{2.2}$$

B. Aggregation model

If the cluster size in n, given this density of clustering, the entropy of data aggregation[8] from equation 2.2. In a lossless mode if there are no faults in the sensor network, 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.



(a) Distributed sensor networks were $\omega_1 = \omega_2$

(b) Passive Clustering were $\omega_1 \neq \omega_2$

Fig. 2. (a) Distributed sensor networks with LEACH single-hop nodes (b) Passive clustering algorithms with multi-hop nodes

C. Local P_{max} functions

Provides a way to determine the local filter value from the probability distribution used by compression algorithms.

$$|Pmax| = \begin{cases} local, & \text{for Pmax} \geq \frac{n}{2} \quad (2.3a) \\ global, & \text{for Pmax} < \frac{n}{2} \quad (2.3b) \end{cases}$$

D. Slepian & Wolf theorem

The Slepian-Wolf rate [10] region for two arbitrarily correlated sources x and y is bounded by the following inequalities, this theorem can be adapted using equation (2.2)

$$R_x \geq H\left(\frac{x}{y}\right), R_y \geq H\left(\frac{y}{x}\right) and\ R_x + R_y \geq H(x,y) \tag{2.4}$$

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 [9]. In our case m=2 as the parameters are distributed whilst collected locally at the cluster head.

III. Compression Rate

A. 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. Equations (3.1-3.4) 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 are 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 2.3(a,b). According to the Slepian-Wolf Theorem [10], established in 1971, that the number of bits needed by using the theorem is lesser, as shown in figure 4(b), than the total entropy for both the two arbitrarily correlated sources $H(x)$, $H(y)$.

$$\begin{vmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \end{vmatrix} = 00 \tag{3.1}$$

$$\begin{vmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \end{vmatrix} = 10 \tag{3.2}$$

$$\begin{vmatrix} 0 & 0 & 1 \\ 1 & 1 & 0 \end{vmatrix} = 01 \tag{3.3}$$

$$\begin{vmatrix} 0 & 1 & 1 \\ 1 & 0 & 0 \end{vmatrix} = 11 \tag{3.4}$$

IV. Fault Rate

Large deployment of sensor network that use an efficient distributed algorithm to select cluster heads which allows to extend the lifetime [4] to function without faults. The fault rate of such an algorithm can be defined as the residual percentage 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 in figure 2 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.

A. Estimate of the sensed value for known densities

Theorem IV.1 *A power law is any polynomial relationship that exhibits the property of scale invariance. The most common power laws relate two variables and have the form.* $PowerLaw = f(x) = ax^2 + o(x)^2$

Proof: The function $f(x)$ is represented as function of transmission distance from the cluster heads to a sink location,

Randomized CH Selection Scheme
Generate a random number $x \in (0, \%CHs)$
Calculate $g_i(x)$ = $P(\omega_i \| \mathbf{x})$ = $\frac{p(\mathbf{x}\|\omega_i)P(\omega_i)}{\sum p(x\|\omega_j)P(\omega_j)} if\, x = rand(x)$
if $x \leq \% then\, CH_i = x,\, else\, CH_i = false$
Threshold CH Selection Scheme
Obtain the sensors residual energy S_j **for all** N_i **neighbors of node i**
Calculate if $\theta \leq S_j$
$g_i(x)$ = $P(\omega_i \| \mathbf{x})$ = $\frac{p(\mathbf{x}\|\omega_i)P(\omega_i)}{\sum p(x\|\omega_j)P(\omega_j)}$ if $x \leq \theta$
$if x \geq \theta$ **then** $CH_i = x,\, else\, CH_i = false$
Optimal Zone based caching Scheme
Divide the sensors into three zones
Use the middle zone as CHs caching
Calculate $g_i(x)$ = $P(\omega_i \| \mathbf{x}) = \frac{p(\mathbf{x}\|\omega_i)P(\omega_i)}{\sum p(x\|\omega_j)P(\omega_j)}$ **if** $x = Constant$
Use optimal settings from the above two cases for % of CHs with use count

Fig. 3. Cluster head selection for power-aware routing in large sensor networks

$f(d)$, where d is the distance to transmit between sensors i to a multihop sensor j towards the sink in increasing distance, from this we get the Power rule [4] based on the distance d of nearest sensor to the farthest away sensor, substituting in the above theorem IV.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 (4.1).

$$PowerLaw = 1^2 + 2^2 + 3^2 + 4^2 + ... + (d-1)^2 + d^2 \quad (4.1)$$

To sum up the total energy consumption we can write it in the form of Power Law equation (4.1.1)

$$PowerLaw = f(x) = ax^2 + o(x)^2 \quad (4.1.1)$$

Substituting d-distance for x and k number of bits transmitted, we equate as in equation (4.1.1).

$$PowerLaw = f(d) = kd^2 + o(d)^2 \quad (4.1.2)$$

$o(d)^2$ is an asymptotically small function of d, Taking Log both sides of equation (4.1.2),

$$\log(f(d)) = 2 \log d + \log k \quad (4.1.3)$$

Notice that the expression in equation (4.1.2) 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. ■

Theorem IV.2 *Properties of power laws - Scale invariance: The main property of power laws that makes them interesting is their scale invariance. Given a relation $f(x) = ax^k$ or, indeed any homogeneous polynomial, scaling the argument x by a constant factor causes only a proportionate scaling of the function itself. From the equation (4.2.1) we can infer that the property is scale invariant even with clustering c nodes in a given radius k.*

Proof:

$$f(d) = kd^2 + o(d^2) \quad (4.2)$$

$$f(cd) = k(cd^2) = c^k f(d) \alpha f(d) \quad (4.2.1)$$

From the equation (4.2.1) 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 [5] obtained in Fig 4 (a) which show optimal results(minimum loading per node[5]) when clustering is $\leq 20\%$ as expected in theorem 1. It is true, however, that the sensor. ■

Theorem IV.3 Theorem 3. *CH Error Rate - Local: If two classes have the same covariance, where $p(x|w_j) \approx N(\mu, \Sigma), j = 1, 2$.*

If prior probabilities are equal, the Bayes model minimizes according to the input distribution and the error rate is given by

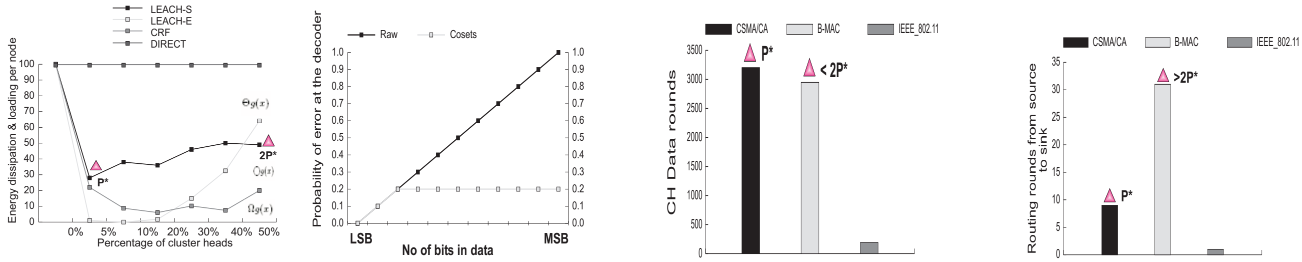
$$P(e) = \frac{1}{\sqrt{[2\pi]}} \int_{r/2}^{\infty} e^{-u^2/2} du \quad (4.3.1)$$

Proof: The simulated algorithms such LEACH use the knowledge that the nodes which are sensing are correlated and have known densities such as cluster size and radio range. The sensed values are i.i.d distributed and their variance $\neq 0$. The underlying model can use the error rate for a cluster as $\frac{1}{c}$ and estimated value θ which is random value of the nodes residual power in this model and is defined by

$$r^2 = \int_{i=1}^{d} \left(\frac{\mu - \mu}{\sigma_i} \right)^2 \quad (4.3.2)$$

where r^2 is the radio range between nodes calculated by using Mahalanobis distance [6]. ■

Theorem IV.4 Theorem 4. *Multi-hop Error rate - Global: When $P(\omega_m|x)$ is close to unity, the nearest-neighbor selection is almost always the same as Bayes selection. This is, when the minimum probability of error is small close to $1/c$, so that all classes are essentially equally likely, the selection made by the nearest-neighbor rule and the Bayes rule are rarely the same, but the probability of error is approximately $1 - 1/c$ for both and is bounded by.*



(a) Fault rate for LEACH lifetime (b) Sensor data fault-redundancy (c) Lifetime Data faults with protocol communications (d) Lifetime Data faults with MAC losses

Fig. 4. Simulation results of fault analysis of WSN routing and data aggregation[8] algorithms

$$P \leq 2P^* \tag{4.4}$$

Proof: We recall that the Bayes decision rule minimizes $P(e)$ by minimizing $P(e\|x)$ for every x. If $P^*(e\|x)$ be the minimum possible value of $P(e\|x)$, and P^* be the minimum possible value of $P(e)$, then

$$P^*(e) = 1 - P(\omega_m|\mathbf{x}) \tag{4.4.1}$$

and from the previous theorem

$$P^* = \int P^*(e|\mathbf{x})p(x)dx \tag{4.4.2}$$

$$P \leq 2P^* \tag{4.4.3}$$

. Convergence of the Nearest Neighbor. ■

V. ANALYSIS OF FAULT RATE CH-ALGORITHMS

A. Estimate of the sensed value for known densities

The simulated routing algorithms such LEACH-S [7], LEACH-E [5] and CRF [5] as described in the above table use the knowledge that the nodes which are sensing are correlated and have known densities such as cluster size and radio range. The sensed values are i.i.d distributed and their variance $\neq 0$. The underlying model uses different ways to select the cluster heads to minimize the error rate. 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[1], the routing algorithms tries to minimize this error criteria. As this model uses the network layer as shown in figure (2a) and the only dependant variable is the fixed lifetime model [4]. The complexity of the algorithm can be defined by using the standard implementation of the LEACH distributed algorithm and its power-aware variations, see table (figure 3).

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

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

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

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-neighborhood rule it uses to find its multi-hop nodes as shown in figure (2b). As the node probability are not known a priori the error rates are much higher than the persistence clustering.

VI. SIMULATION

A. 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 shows number of cluster heads and the fault rate for distributed clustering and passive clustering in figure 4. Simulation results confirms the fault rate is network size invariant and converges to the optimal values derived in theorem 1 and 2.

TABLE I
SUMMARY OF NOTATIONS FOR ANALYSIS OF ROUTING FAULT-RATE

Symbols	Definition
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 energy
CH	Cluster head
$P(\omega_i\|\mathbf{x})$	Conditional probability
$P(\mathbf{x}\|\omega_i)$	Class conditional probability

B. Results from the MAC layer

When node densities are not know in advance due to node failures or unscheduled 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 [6] 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

MAC_{LESS} Cross Layer Simulation Bayesian fault rate Fixed Energy Model	$\omega_1 = \omega_2$	$\omega_1 \neq \omega_2$,	Assumptions	MAC_{LOSSES} Protocol Simulations Bayesian fault rate Renewable Energy Model	$\omega_1 = \omega_2$	$\omega_1 \neq \omega_2$	Assumptions
LEACH	0.27%	0.41%	2^m where m=2 faulty bits	SPEED-CSMA	0.3%	0.1%	BER, GlomoSIM radio
Fixed Energy	$\omega \leq 20\%$	$P = 2P^*$	Optimal config, Theorem 1,2	SPEED-BMAC	0.1%	0.1%	BER, GlomoSIM radio
Node failures(renewable lifetime)	x	$P \leq 2P^*$	Errors due to unbalanced nodes	Renewable Energy Model	x	$P \geq 2P^*$	Node failures. Theorem 3,4
				Channel Error Model	$P = P^*$	$P \geq 2P^*$	Link errors. Theorem 3,4

Fig. 5. Simulation test-bed for power-aware lifetime models

coordinates specified by x:

$$P^*(e) = \int P(e|x)p(x)dx \tag{6.1}$$

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

$$P = P^* \tag{6.2}$$

For passive clustering is given by

$$P = 2P^* \tag{6.3}$$

As shown in figure 2(a) 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 as shown in 2(b) the node densities are unknown in this case due to high likely-hood of faults. The protocol simulation results are show in table (figure 5) that the upper bound has error rate of P(e)=0.41% which converges to the proof derived in theorem 3 and theorem 4 and the upper bound in figure 1(c), chapter 4 on non parametric techniques [6].

C. 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 [3] bit error rate(BER) simulator and implement the routing algorithms for multi-hop cases. The routing algorithm implemented is SPEED which as shown in table (figure 5) is a geographic routing algorithm which uses two dimensional coordinate space to calculate the path from the node coordinates. Many runs into the protocol simulation suggest that the radio characterization for CSMA [3] and B-MAC are comparable, figure 4(c) when the node densities are known. The radio characterization for CSMA [3] is prone to faults when compared to B-MAC, figure 4(d) 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 in B-MAC when compared to CSMA and error rates are $P \geq 2P^*$ higher than the theoretical Bayesian limit [6] of $P = 2P^*$ as derived in theorem 3 and theorem 4.

VII. Conclusion

In this paper we study Bayesian model to predict the theoretical bounds and compares with real simulations of cross-layer and protocol implementations using power-ware MACS. To have a reliable sensor network for MAC's using renewable energy resources, from the simulation results, the implemented protocols adapts well for denser configuration as the base configuration has errors greater than the theoretical limits.

VIII. Acknowledgments

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