Effects of channel SNR in Mobile Cognitive Radios and Coexisting Deployment of Cognitive Wireless Sensor Networks

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Abstract—**In this paper, we describe the cognitive radios sharing the spectrum with licensed users and its effects on operational coexistence with unlicensed users. Due to the unlicensed spectrum band growing needs and usage by many IEEE 802.11 protocols, normal wireless radio operation sees high interference leading to high error rates on operational environments. We study the licensed bands and the characteristics of the unlicensed bands in general and more specific to radio characterization of individual radios and cognitive deployment of sensor networks and its effect on lifetime. The cognitive radio signals detection algorithm for this probabilistic model for the unlicensed users, uses a mobility model which takes into account the threshold variable ratio $\frac{E_b}{N_o}$ and also calculates the lower-bound of the combined value of secondary user interference for overlapping frequencies with the primary user. By using simulation, we detect the primary user when the radio frequencies are known a priori and compare it when the frequencies are unknown. In our analysis we exploit the similarity measure seen at each sub-channel frequency, which are due to multiple paths of the same reflected signal by maximizing the correlated information of the correlation matrix. For the general case the co-variance matrix for blind source separation, we use ICA de-correlation methods and show that cognitive radio can efficiently identify users in complex situations. The effects of large deployment and cognitive sensor network are studied for a family of 802.15.4 radios adapting to power-aware algorithms.**

Index Terms—**Algorithm complexity, SDR and Cognitive Radios, Power Aware Radios, Cognitive Wireless Sensor Network, Covariance Matrix, PCA, ICA.**

I. Introduction

Cognitive radio and sensor network studied here are both considered static, with mobile primary licensed users. There are mobile primary users model for extensions to study specific signal estimation techniques. The cognition in their part has two common modes of interference avoidance. The first approach uses overlay to make up for the unused spectrum bandwidth and the second approach uses underlay in the form of interference control. The history of cognitive radio can be attributed to the thesis work of J. Mitola in 2000, where he coined "Cognitive Radio" for a form of radio that would change its performance by detecting its environment and changing accordingly. Using mobility frame work and cognitive radios we find the trade-offs between minimum spectrum power allocation and channel rate, when operating in overlapping frequencies with primary users.

We like to study the performance of deploying for dense Wireless Sensor Networks which uses the ISM band using IEEE 802.15.4 protocol in context of Cognitive networks. Due to recent emerging standards on inter-operability but none of them address the distributed nature of the spectrum. Some of the deployments have adapted to frequency reuse and orthogonal spectrum allocations to have least interference and better usage of the same spectrum. These implementations allow baseline reality and also taking into consideration of the non-linearity of the radios in practice which introduce errors during channel coding. In this paper we extend radio interpretability and its specific power-ware requirements for extending the sensor network lifetime. We model interference as unlicensed users partially overlapping with primary user as shown in Figure 1, using a

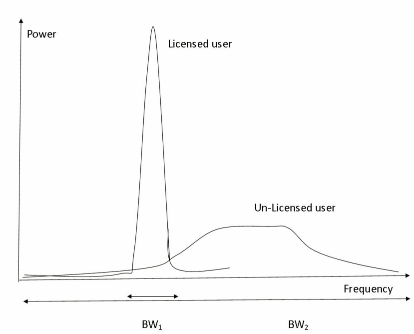

Fig. 1. Frequency and Bandwidth of Unlicensed user partially overlapping with primary user.

simulator ad illustrated in Figures 2, 3 and 6, which give raise to co-channel interference. The varying parameters at the radio receivers are interference due number of overlapping channels and variation caused by mobility. The interference in mobility can be seen as the phase shift due to Doppler and phase shift leading to delay spread due frequency. The two dimensional representation of interference varying with wireless range from the primary signal and the interfering signals is represented using co-variance matrix. The correlated channels with high signal to noise ratio (SNR) have better Qos, which leads to higher link quality and interference free reception during spectrum usage.

The paper is organized into: Section II describe related work in these emerging standards. In Section III, we outline architecture of the Cognitive Radio Model using Interference avoidance (spectrum-overlay) and crosslayer stack and its effects of sensor network protocols. In Section IV, the Rayleigh fading model is described in terms of mobility patterns and how it can be represented as a two-dimensional co-variance matrix. Wireless Cognitive networks comparisons are included in Section V, sensor network life-time Vs interference is studies for 802.15.4 radios. Concluding section on mobility simulated results describe the upper and lower-bound detection thresholds for maximizing co-variance and ICA [7] for selecting optimal range and SNR for the primary user. The secondary users which are coexisting sensor networks, we discuss lifetime performance and routing protocols in the context of static cognitive networks.

II. RELATED STANDARDS

Due to the availability of Software Defined Radios (SDR) and its ability to architect sophisticated spectrum sensing radios, the FCC in 2004 formed a working group to define 802.22 standards. The new standard was particularly to rural areas by sharing the television spectrum, the standard is expected to be completed by the first quarter of 2010 and with this some of the first networks could be deployed.

There are a number of elements that were set down for the basis of the 802.22 standard. These include items such as the system topology, system capacity and the projected coverage for the system. By setting these basic system parameters in place, the other areas fall into place. The model selection [8] for this work studies the radio performance based on mobility and the protocol performance due to interference in dense sensor networks. The crosslayer stack parameters which effect such channel capacity, SNR, energy efficiency, BER and optimum radio modulation schemes for a given interference level to exist with other radios is described in Theorem 1 through Theorem 7.

III. MODEL PREDICTION

A. Interference avoidance (spectrum overlay)

Using the specification of 802.22, which rely on a central command controller, it would allow the base station to have large training samples collected from all the CPE's. The data-set can be used over time to predict the spectrum availability for cooperative future scheduling. The spectrum can be categorized into highly, medium and sparsely used. We expect the coverage in urban areas, where the network may be deployed would fall into the sparse spectrum category. The CPE's which are deployed remotely will collect the frequency of the detected signal and its time duration in its overlapping spectrum. The spectrum availability can be calculated with the overlapping intervals. Current radio designs uses packed based count [2] and time-sampling [2] techniques. In the packed capture technique, the cognitive module becomes quite complex due to large number of packets and its demanding space requirements. In the other implementation Systematic Timer based Sampling (STT), all the channels are sampled at an interval of 1 second and provides an accurate measure of the spectrum activity to be recorded. The above techniques takes into account the capture of packets over the entire networks and uses cognitive network techniques.

In this paper, we discuss how to represent data-sets in two-dimensions which model the interference and the path-loss models for cognitive radio co-existence. These dynamic channel losses are used to de-correlate the signals of the primary and secondary users.

B. IT Model (spectrum underlay)

The concept of interference temperature [1] is identical to that of noise temperature. It is a measure of the power and bandwidth occupied by interference. Interference temperature T_I is specified in Kevin and is defined as

$$T_I(f_c, B) = \frac{P_I(f_c, B)}{kB} \tag{1}$$

where $P_I(f_c, B)$ is the average interference power in Watts centered at f_c, covering bandwidth B measured in Hertz. Boltzmann's [1] constant k is $1:38 \times 10^{-23}$.

C. Ideal Model-Known Frequencies

In the ideal interference temperature model we attempt to compute only the interference due to licensed signals. Assume our unlicensed transmitter is operating with average power P, and frequency f_c, with bandwidth B. Assuming that the radio knows the frequencies of the base station and the allowed bandwidth, then it needs to only filter frequencies in the range $f_c - B/2 + f_c + B/2$ overlaps n licensed signals, with respective frequencies and bandwidth of f_i and B_i.

As shown in Figure 1, we need to guarantee that

$$T_I(f_i, B_i) + \frac{M_i P}{kB_i} \leq T_L f_i, 1 \leq i \leq n \tag{2}$$

Note the introduction of constants M_i. This is a fractional value between 0 and 10 as shown in Table I, representing a multiplicative attenuation due to fading and path loss between the unlicensed transmitter and the licensed receiver. Section II described the 802.11 standard, which allows to define the licensed user. The model co-existing needs only to know which are the overlapping frequencies other than the given standard specification of frequency and bandwidth. The second step is to measure T_I in the presence of the licensed signal. Assuming us know the signal characteristics and the wireless losses we can use correlation of the measured interference, which will help isolate the redundant signal interference. Also, if we have precise knowledge of the signal's bandwidth B and center frequency f_c, we can approximate the interference temperature

$$T_I(f_c, B) \approx \frac{P(f_c - B/2 - \tau) + P(f_c + B/2 + \tau)}{2kB} \quad (3)$$

where $P(f)$ is the sensed signal power at frequency f and τ is a safety margin of a few kHz.

D. Generalized Model-Unknown Frequencies

In cases where there are no prior knowledge, which could be a new network environment then, we need to apply interference temperature model to the entire frequency range of operation to detect any primary user. This is typically the case with blind source separation.

$$T_I(f_c, B) + \frac{MP}{kB} \leq T_L f_c \quad (4)$$

Assuming each licensed signal has power P_i and otherwise the interference floor is defined by the thermal noise temperature T_N, we can transform (4) into the following:

$$KBT_L(f_c(B - B_i) + kBT_N \Sigma_{j=1}^{n} B_j \leq \Sigma_{j=1}^{n} B_j P_j \forall 1 \leq i \leq n \quad (5)$$

In a simple case with only one licensed receiver, the inequality simplifies to

$$\frac{KBT_L}{P_1 - kBT_N} \leq \frac{B_1}{B - B_1} \quad (6)$$

Latter in the result analysis we show how to measure and de-correlate in such complex environments.

E. Crosslayer STACK Model

Sensor nodes and its communication stack have limited resources per node and replacement of nodes or batteries may not be practical. Placement and deployment of sensors need to accounted for optimal coverage and the needed density of sensors for reliable calibration of the measured values. We use a crosslayer model due to the nature of wireless as the sensor connectivity is not always available. The crosslayer architecture allows to account for energy dissipated at each level during the entire lifetime, so that the power-aware protocols can adapt the radios for optimal coverage and longer useful lifetime.

IV. Modeling Mobility in Wireless Channels

Rayleigh fading is used to describe the characteristic of the wireless channels, which are used by wireless receivers. The Rayleigh model assumes that signal has passed through such a medium and will vary randomly or fade according to Rayleigh model. The Doppler power spectral density of a fading channel describes how much spectral broadening it causes. The effect on pure signal, when it passes through such a channel.

$$S_\nu = \frac{1}{\pi f_d \sqrt{1 - \left(\frac{\nu}{f_d}\right)^2}} \quad (7)$$

Where ν is the frequency shift relative to the carrier frequency. The equation is valid only for values of ν between $\pm f_d$. The Doppler model as shown in equation (7) and the Rayleigh model described here and in equation (8), we can extend it to simulate mobility by summing up the sinusoidal. The calculation of the co-efficient of the real and imaginary parts used by the Rayleigh model can be redefined for a scatter, which is uniformly distributed around a circle at angles α_n with k rays emerging from each scatter.

In the described model we use multiple radio receivers $R_p, R_{s1}, R_{s2}...R_{sm}$. The normalized autocorrelation function of a Rayleigh faded channel with motion at a constant velocity is a zeroth-order Bessel function of the first kind:

$$R\tau = J_0(2\pi f_d \tau) \quad (8)$$

A. Level Crossing Rate

The level crossing rate is a measure of the rapidity of the fading. It quantifies how often the fading crosses some threshold, usually in the positive-going direction. For Rayleigh fading, the level crossing rate is:

$$LCR = 2\pi f_d \rho \exp^{-\rho^2} \quad (9)$$

where f_d is the maximum Doppler shift and ρ is the threshold level normalized to the root mean square (RMS) signal level:

$$\rho = \frac{R_{thresh}}{R_{rms}} \quad (10)$$

Let us design a way to detect and isolate the primary user R_p and a secondary users $R_{s1}, R_{s2}...R_{sm}$ for channels $ch_1, ch_2, ch_3...ch_{48}$. For single mobile receivers the interference noise due to path-loss has a single spike, but for multiple users the interference noise due to path-loss degrades into a Gaussian curve [5]. From equation (2), we calculate a values M_i for the interference seen at multiple channels in time.

$$M_{cov} = \begin{pmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{pmatrix} \quad (11)$$

To maximize the correlation we need to optimally select the diagonal elements of the matrix shown in equation (11) and values in Table I, such that the equation below (12) can be used to select channels which can differenti-

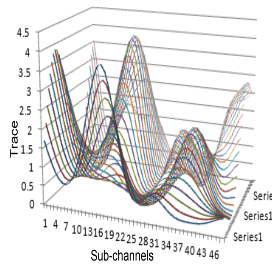

Fig. 2. Ideal primary user model - 1-frequency and varying position in time (in timestamp) for a mobile node.

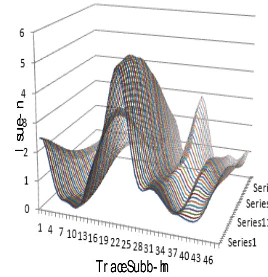

Fig. 3. General user model - Primary user with coexisting static secondary users 2-frequencies varying position in time of the primary user (in timestamp).

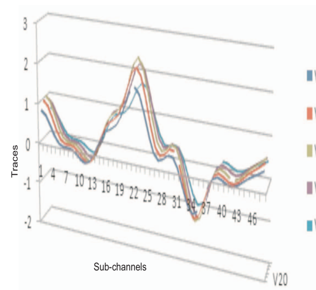

Fig. 4. Tracking SNR ρ_{cor} co-efficient in PCA (measured in SNR) of the optimal correlated channels.

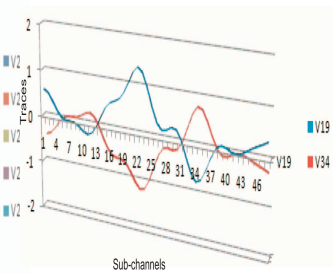

Fig. 5. Separating SNR ρ_{uncor} co-efficient in ICA (measured in SNR) of uncorrelated and unknown source frequencies.

TABLE I
PEAK SNR MEASURED VALUES OF THE DIAGONAL ELEMENTS FROM THE COMPLETE DATA SETS. (METHOD1 COMPARED WITH METHOD2)

Values of $\rho_{i,j}$	Measured M_{Hi}	Measured M_{low}	Ideal Upper-Bound	Ideal Lower-Bound	General Upper Bound	General Lower Bound
ρ_{cor}=1.313362745	3.792	0.08	0.46	0.32	1.41028417	1.22920039
ρ_{cor}=1.3747417	4.362	0.022	1.821411	0.345488	2.0216711	-1.22920039
ρ_{cor}=2.07415429	4.222	0.034	2.235424	0.415796	2.0216711	0.8926338
ρ_{cor}=2.086886414	3.917	0.063	2.229352	0.530349	2.3109796	0.21394222
ρ_{cor}=2.420906219	4.073	0.047	2.420906	0.09	2.7578501	-0.74375612
ρ_{uncor}=0.816974583	4.362	0.013	1.399701	0.320941	1.30032658	0.03084368

ate primary user from the secondary user's interference.

$$G = \max det(M) = \rho_{11} = \rho_{22} = 1 \tag{12}$$

V. SENSOR NETWORK LIFE-TIME VS INTERFERENCE

Sensor networks standards are placed at the low power range of the spectrum and use overlapping frequencies of the unlicensed ISM sub-channels bands. Typically the range of sensor radios are limited and tend to be deployed in dense configuration for maximal sensing coverage. Multi-hop broadcast nature of the wireless channel the sensor network protocols uses channel access protocols to avoid collisions. We study difference channel access protocols and its effect on dense deployments. The lifetime of sensor networks would be shorted due to loss of energy at the protocol level due to collisions, retries due to pathloss errors and idle listening. If a distributed protocol is used then the depletion of energy at the node are due to over usage of its limited energy reserves, which happens when routing algorithms use distance vector metric instead of power-aware metrics. The system suffers from energy holes which ultimately partition the network rendering the quality of the data from the networks inaccurate as it represents a small count of the overall connected sensors.

The lifetime of the sensor network can be represented by the equation below,

$$Lifetime = \frac{C_{batt} \times V \times 60 \times 60}{Energy_{Tx} + Energy_{Rx} + Energy_{Idle} + Energy_{Listen}} \tag{13}$$

it uses minimal energy when not transmitting. Most of the IEEE 802.15.4 radios use power-aware protocol which efficiently duty-cycle using sleep modes. Due to the nature of energy saving at every level of the stack, cross-layer optimization is an important aspect of scalable sensor network. We study the lifetime by optimizing the necessary protocols to allow longer lifetime.

A. Distributed Model with Radio abstraction

Power-aware distributed protocols works directly at the routing layer, this allows to rotate the cluster heads periodically from a percentage of nodes in the network. MAC and radio abstraction is assumed and only TDMA based synchronization is needed to coordinate the nodes. The protocol allows to configure the percentage of nodes to be elected as cluster head, which essentially acts like router and other nodes are configured to aggregate the data to minimize the number of bits needed for transmission. Due to distributed nature of selecting the cluster heads (transmitters) the average energy consumed is reduced compared to traditional routing protocols. As transmission uses most of the energy in the protocol, it allows to maximize the lifetime of the sensor network, before a node fails due to energy depletion. Routing protocol over head is more than lower layer protocols as it needs to have higher level of the topology for synchronization.

$$CH_{Lifetime} = T_{transmit} + T_{receive} \tag{14}$$

$$Node_{Lifetime} = T_{receive} \tag{15}$$

B. Single hop Model with best effort 802.11 Radio scheduling

The 802.11 radios have three states Transmit (Tx), Receive (Rx) and Idle, the communication protocols spend a percentage of time depending on the ambient events. The MAC protocol uses lower layers for neighborhood discovery and communication and has very low overhead. The physical layer protocol does not do well with data aggregation as in the case of time coordinated LEACH, which does not improve the reliability of the sensor network.

$$Node_{Lifetime} = T_{transmit} + T_{receive} + T_{listen} + T_{Idle} \quad (16)$$

C. Multi hop Model with Sync 802.15.4 Radio scheduling

The 802.15.4 is designed from the physical layer where the sensors are calibrated. Due to the nature of the wireless false events can get transmitted due to high floor noise. Sensor MAC protocols are specifically designed adapt to ambient operating environment, this includes averaging the floor noise and using a link layer based approach to data aggregation. The MAC radios are designed to be receiver centric as the sensor network protocols spend more time sleeping and idling during its lifetime. The protocols extends the single hop discussed earlier to multi-hop by using a sync packet, which allows to schedule forwarding nodes and wakes up during the next time the transmission is probable.

$$Node_{Lifetime} = T_{transmit} + T_{receive} + T_{listen} + T_{Idle} + T_{Sleep} \quad (17)$$

The detection of the secondary user transmitter is ensured at the forwarding receiver nodes, which allow enough number of nodes to awakened during the broadcast enabling synchronization. A beacon is implemented part of low-power listening (LPL) radios synchronization for the next hop routing nodes. For reliable synchronization the transmitting wakeup beacon is twice the period as compared to the LPL radio active period. Amortized dissipation

$$= \frac{Energy_{Tx} + Energy_{Rx} + Energy_{Idle}}{3} \quad (18)$$

VI. Simulation

The simulation is set to analyze two fundamental aspects of cognition, one to identify the source signal of that of a primary user during mobility as illustrated in Figure 6, noise due to path loss and with interference due to secondary users and the second one is to maximize the lifetime of a large network by using minimum power. Table II define the detection algorithms for cognitive radio and Table III defines the crosslayer protocol models used by cognitive wireless sensor network.

A. Mobility and cognitive radio subchannels

IT models described in equation (2), we calculate different values for the variable terms $T_I(f_i, B_i)$ and $\frac{M_i P}{k B_i}$. A OMNET mobility framework simulator, uses

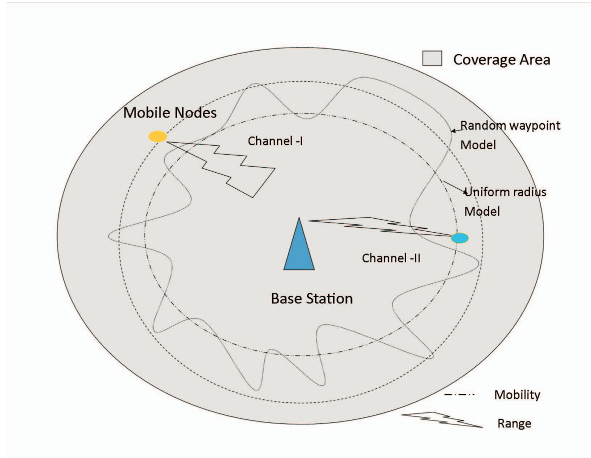

Fig. 6. Mobility framework and wireless channel for calculating pathloss.

TABLE II
COGNITIVE RADIO CHANNEL INTERFERENCE SIMULATION SETUP

Methods	Model	Metric
Mobility Traces	OMNET++	Doppler
Propagation	Rayleigh-Jake's	Phase, freq
Radios	1 Primary user	T_I Cognitive
Channel	48 Sub-channels	M_i
Noise	1 Secondary user	Floor-noise
Covariance	R Project for Statistical Computing	ρ_{cov}
ICA	R Project for Statistical Computing	ρ_{uncov}

interference modeling as derived in Section IV and Table III. We use two models to analyze the data collected from the mobility simulator, one uses the co-variance technique [4,6] to optimize as shown in equation (12), when there is not too much of co-channel interference is seen the second method uses ICA, which de-correlates under the presence of heavy co-channel interference.

B. Two Dimensional Representation of Interference using Covariance

The Figure 2 shows different values of M_i seen at the primary receiver with no secondary users, as it can be seen that it has unique peaks, which vary in time. It is seen that the convolution of two Gaussian functions is again a normal Gaussian function, and thus the distribution for the sum of two independent normal random variables is again normal. If they are independent, their joint distribution [7] has the form of

$$p(x) = \prod_{i=1}^{d} p(x_i) = \prod_{i=1}^{d} \frac{1}{2\pi\sigma_i} e^{-1/2((x_i-\mu_i)/\sigma_i)^2} \quad (19)$$

The measured interference due to mobility and spectrum interference due to overlapping with n licensed bands over time, $d = 48$, see simulation section and Table I.

$$= \frac{1}{(2\pi)^{d/2} \prod_{i=1}^{d} \sigma_i} = exp \left[-\frac{1}{2} \prod_{i=1}^{d} \left(\frac{x_i - \mu_i}{\sigma_i} \right)^2 \right] \quad (20)$$

This can be written in a compact matrix form if we observe that for this case the co-variance matrix is diagonal, this is,

$$\Sigma = \begin{pmatrix} \rho_1 & 0 & .. & 0 \\ 0 & \rho_2 & .. & 0 \\ : & : & \searrow & : \\ 0 & 0 & .. & \rho_d \end{pmatrix} \quad (21)$$

The measured co-efficient are shown in columns of Table I and the corresponding co-variances are calculated in calculated columns of the current table. Initially, when only the primary user is using the spectrum and has mobility with constant fading and changing wireless range, the signals seen at the receiver has a sharp spike which is shown in Figure 2. The corresponding Figures 3 shows the effects of interference at the primary receiver, the plot do not have any spatial or time varying properties, as it is uniformly distributed, which follows a Gaussian distribution. To separate the interference from the secondary users, we need to compute the lower and upper bounds of the interference floor, which is computed by the thermal noise temperature T_N. The co-efficient of the co-variance matrix of all the 5 data-sets are chosen to maximize G as shown in Table I. As we to use the correlation between signals, which are due to multi-path scattering, we plot the upper bound response of the attenuation of the channels, this is shown in Figure 4, which is seen completely correlated and described in equation (3).

C. Estimation of Interference using ICA

The above method uses correlation matrix to maximize the determinant to find the primary user and secondary users. ICA uses a method which seeks components, which are varying independently and thus differentiates the primary user and the rest. This method is preferred when the noise level is very high in the channels. The measured coefficients for ICA analysis using R-System package fastICA [3], are tabulated in Table I(ICA_1, ICA_2, where users=2), $\rho_{uncorr} = 1.30032658$ for number of signal equal to two, which are approximately lower bound of the last result set $\rho_{corr} = 1.313362745$. Figure 5 shows how ICA can perform well when the sources are unknown and blind or shadowed to measurements, when the noise level is above the given interference threshold, as shown in equation (6).

D. Crosslayer stack and cognitive sensor network

The previous method uses cognitive radio approach and hence more accurate at the node level and we have shown it can perform well in cases of node mobility and blind source separation. In our experiment we assume a large scale deployment of at least few hundred nodes and the protocol will scale up to thousand of nodes. The sensor networks protocols are broadly divided into distributed and MAC layer protocol. The use of distributed routing allows to calculate the upper bound performance using equation (14) and the best effort mode which uses the MAC allows to calculate the lower bound as the protocol designer has more option to adapt to traffic patterns. In the case of distributed protocols the x-axis as illustrated in Figure 7, represent the number of cluster heads, which can be varied and the y-axis represents the average energy dissipation during its entire lifetime. In the case of the MAC protocol, which has the radio states part of the communication protocol it can further adapt. Our experiment measures the energy consumption of the radio as defined in equation (13), the x-axis represents many channel access protocols as illustrated in Figures 8 and 9. The y-axis represents the lifetime in seconds for a large deployment. In our experiments, the performance of the clustering based protocols do well when the percentage of cluster heads are less than 20% of the total network size. In the best effort mode the protocols which use multi-hop routing, does well in terms of overall reliability and network throughput.

TABLE III
SIMULATION SETUP OF 802.15.4 COGNITIVE WSN NETWORK

Stack Methods	MAC Model	Routing Metric
Radio abstraction	Distributed	Cluster Heads
Best effort	Single-hop	Channel control
Best effort	Multi-hop	LPL
Best effort	Multi-hop	Sync

E. Dense Deployment and Channel Interference

Figures 10 and 11 shows how radio idling and fixed range radios in dense deployment further effects the overall performance in a negative way.

VII. CONCLUSIONS

Cognitive radio and its role for coexisting with a spectrum have been emphasized with evolving standards. Most of our experiments where done at the cognitive radio layer, which allows to closely design the algorithms for signal detection and also use power-aware protocols to manage the radios. In the power-aware signal analysis we compare the ideal spectrum model with the generalized spectrum model to obtain upper and lower bounds of the thermal interference for the variable frequency range of primary user. We improvise by calculating the floor noise due to co-channel interference and detecting the primary user with least power as in the case of 802.22 standards. To find the performance of our method, when the primary user frequencies are unknown which are the case in wireless sensor networks, we compute ICA for

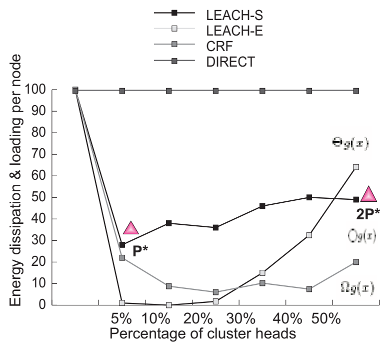

Fig. 7. Distributed WSN Model in time (in routing rounds) .

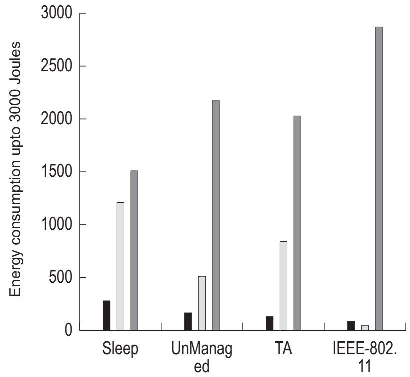

Fig. 8. 802.11 WSN MAC in time (in lifetime seconds) .

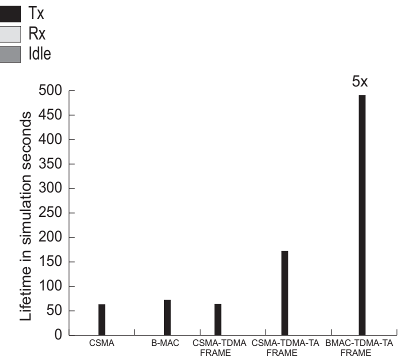

Fig. 9. Multi-hop WSN MAC in time (in lifetime seconds) .

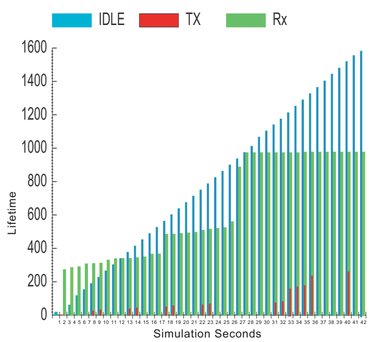

Fig. 10. Startup Radio energy characterization in time (in seconds).

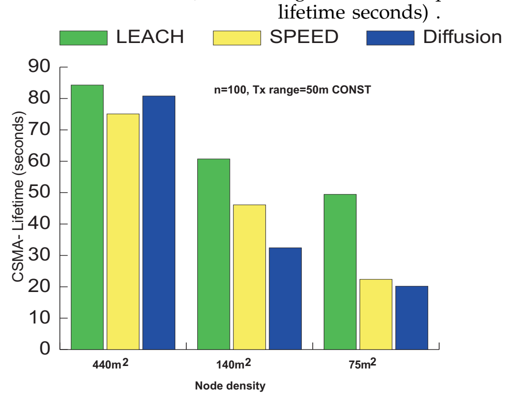

Fig. 11. Radio Range Interference - Low, Medium and High deployment density in time (in lifetime seconds) .

the entire spectrum and show that the primary user detection is possible when coexisting with secondary users or when noise dominates the desired feature thresholds. The deployment strategies of sensor networks allow to compare other detection methods specially in dense overlapping of the lower end spectrum usage.

VIII. Acknowledgements

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IX. Interference Vs Energy Model

Theorem 1

- *Co-channel Interference*

$$SIR = 10\log_{10}\left[\left(\frac{D}{R}\right)^n K_l^{-l}\right] \tag{22}$$

Gaussian Model

- *Adjacent Channel Interference*

$$SIR = C\frac{P_{TX}}{d^n}\left(\frac{P'_{TX}\int_w G(f)df}{(d)^n}\right)^{-1} \tag{23}$$

Transmitter sensitive

- *Multi-path fading*

$$\cos(2\Pi ft+\theta) \Rightarrow Doppler\ Spectrum\ Model \tag{24}$$

The effects of fading θ can be combated by using diversity to transmit the signal over multiple channels that experience independent fading and coherently combining them at the receiver. The probability of experiencing a fade in this composite channel is then proportional to the probability that all the component channels simultaneously experience a fade, a much more unlikely event.

For the IT model described in equation (2), we calculate different values for the variable terms $T_I(f_i, B_i)$ and $\frac{M_iP}{kB_i}$. The reliability of a digital system is measured in terms of the error rate in the transmission link. BER - Bit Error Rate, SER - Symbol Error Rate, FER - Frame Error Rate, PER - Packet Error Rate. The SER characterizes the performance of the modulator. The BER is measured at the bit-level in terms of the number of bits that are received erroneously.

A. Channel Capacity

Theorem 2 *Shannon showed that in an AWGN channel, the maximum bit-rate C that can be achieved with arbitrarily low error rate over a given transmission bandwidth WT is bounded by the expression below:*

$$E_b = \frac{E_s}{\log_2 M} \tag{25}$$

$$\bar{E_b} = \sum \frac{p_i E_s^i}{\log_2 M} \tag{26}$$

where p_i is the probability for the occurrence of the i^{th} symbol with energy.

$$E_b = \frac{max E_s^i}{\log_2 M} \tag{27}$$

Theorem 3 *Where E_b is expressed in terms of the peak symbol energy in the signal constellation. E_s^i. where $\gamma = E_b$ and $\bar{\gamma} = \bar{E_b}$*

$$\frac{C}{W_T} \leq \log_2\left(1 + \frac{P}{N_o W_T}\right) = \log_2\left(1 + \bar{\gamma}\frac{C}{W_T}\right) \tag{28}$$

Symbol Energy:

$$E_b = \frac{E}{\log_2 M} \tag{29}$$

where $P/N_o W_r$ is the SNR, C/W_T is the maximum achievable bandwidth efficiency in bps/Hz, and γ is the average E_o/N_o defined by equation (2).

B. Error Rate Bounds.

Theorem 4 *SER on the otherhand is measured at the symbol level in terms of the number of symbols that are in error. A symbol error is made when the received signal falls outside of its decision region. A symbol error leads to a bit errors as the symbol is erroneously mapped to an incorrect bit-pattern. Let n be the number of bits per symbol. Then, SER may be bounded in terms of BER as shown below:*

$$P_b \leq P_s \leq n.P_s \tag{30}$$

To express PER in terms of BER

$$P_p = 1 - \left(1 - P_b^{L_p}\right) \tag{31}$$

C. A basic measure using BER

Theorem 5 *SER, FER, and PER all depend on BER, a basic measure for digital system is based on BER which can be expressed in terms of $\frac{E_b}{N_o}$, where E_b is the energy per bit and N_o is the equivalent noise spectral density over the signal bandwidth. The variations of BER with $\frac{E_b}{N_o}$ depends on the channel and the type of the demodulator. Channel Models:(see Table IV for BPSK-modulation)*

- *AWGN*

$$P_b = Q\left(\sqrt{\frac{2E_b}{N_o}}\right) \tag{32}$$

- *Rayleigh Fading*

$$P_b = \frac{1}{2}\left(1 - \frac{\sqrt{E_b/N_o}}{1 + E_b/N_o}\right) \approx \frac{1}{4E_b/N_o} \tag{33}$$

D. Design goals for using BER

Theorem 6 *Additive white Gaussian noise (AWGN) in general, in an channel, BER is exponentially related to E_b/N_o, while in a fading channel, BER is inversely related to E_b/N_o.*

For a given BER, a digital system with lower $\frac{E_b}{N_o}$ requires lower transmission power, which can improve battery lifetime of the communication device and the system capacity.

E. Energy Efficiency

Theorem 7 *Energy efficiency can be more accurately defined, when taking into account both energy and bandwidth, we define $f(x)$ of a system to be the amount of E_b/N_o required for a given bandwidth efficiency:*

TABLE IV
ENERGY EFFICIENCY COMPARISON USED BY RADIOS

BPSK	9.09	1	11.0
GMSK	10.8	1.35	11.5
QPSK	9.09	2	16.5
8-PSK	19.82	3	11.8
16-PSK	55.41	4	6.8
32-PSK	171.2	5	3.6
8-QAM	13.93	3	16.8
BFSK	17.78	1	5.6

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