

Performance Evaluation of Energy Efficient Modulation Scheme and Hop Distance Estimation for WSN

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Abstract: A Wireless Sensor Network is composed of hundreds or thousands of nodes that can be equipped with limited energy resources but can still be used over an extensive set of diverse applications such as environment monitoring, healthcare, homeland security, military surveillance, manufacturing, and industry automation. The physical layer parameter affects the performance of the network. In this circumstance, we analyze the best modulation scheme, and transmission approach to minimize the total energy consumption required to send a given number of bits. The total energy consumption includes both the transmission energy and the circuit energy consumption. The modulation schemes are compared based on their energy consumptions at their transmitting node. We consider hop distance estimation for latency analysis. The hop distance estimation used to find the minimum number of hops required to relay a packet from one node to another node in a random network by statistical method. From the minimum number of hops, we have calculated the energy consumption and latency. The statistical model is compared with two other linear models. The result obtained shows that, the statistical method yields a better result for all the performance parameters.

Keywords: Physical layer, Energy consumption, Latency, Modulation scheme, Hop estimation, NS-2

[1] 1. Introduction

Wireless Sensor Networks typically consists of a large number of sensor nodes distributed over a certain region. The radio frequency (RF) transceiver, A/D and D/A converters, baseband processors, and other application interfaces into one device which is called as sensor node. These sensor nodes are characterized by their low power, small size and cheap price. Thus, in many scenarios, the wireless nodes must operate without battery replacement for many years. Consequently, minimizing the energy consumption is a very important design consideration, and energy-efficient transmission schemes must be used for the data transfer in sensor networks. They actually transform the data into electric signals, which are then processed to reveal some of the characteristics about the phenomena located in the area around the sensors.

Some authors are addressed the problems in physical layer, network and MAC layer [1 – 12]. Akyildiz et al [1], a survey of state-of-the-art routing techniques in WSNs has been presented along with the sensor node communication architecture and protocol architecture. Overall, the routing techniques are classified into three categories based on the

underlying network structure. The design trade-offs between energy and communication overhead savings in every routing paradigm has been discussed.

Eugene Shih et al [2] have proposed a physical layer driven approach to designing protocols and algorithms. But they not addressed the latency. Heinzelman et al [3] have analyzed the low-energy adaptive clustering hierarchy (LEACH), a protocol architecture for micro sensor networks that combines the ideas of energy-efficient cluster-based routing. The results of this paper show that LEACH can improve system lifetime by an order of magnitude compared with general-purpose multihop approaches.

J. Goldsmith et al [6] have considered wireless systems where the nodes operate on batteries so that energy consumption must be minimized while satisfying given throughput and delay requirements. Ekici et al [7] have proposed a secure probabilistic location verification method for randomly deployed dense sensor networks.

Amitabh Basu et al [10] study the problem of localization with noisy distance and angle information. With no noise at all, the localization problem with both angle and distance information is trivial. A mobile-assisted localization (MAL) method [11] which employs a mobile user to assist in measuring distances between node pairs until these distance constraints form a “globally rigid” structure that guarantees a unique localization.

[2] 2. Modulation Scheme

Modulation is the process coding of information onto the carrier frequency. This includes amplitude, frequency, or phase. It is done to send the information over the long distance. The modulation scheme used by the radio is important factor which strongly impact the energy consumption of the node. The different types of modulation schemes include Amplitude Shift Keying, Frequency Shift Keying and Phase Shift Keying.

2.1 Binary Vs M-ary QAM

In binary modulation we can transmit only bit 0 or 1 per symbol where as in M-ary modulation we can transmit multiple symbols per bit. One way to increase the energy efficiency of communication is to reduce the transmit time of the radio. This can be accomplished by sending multiple bits per symbol, that is, by using M-ary modulation. Using M-ary modulation, however, will increase the circuit

complexity and power consumption of the radio. In addition, when M -ary modulation is used, the efficiency of the power amplifier is also reduced. This implies that more power will be needed to obtain reasonable levels of transmit output power. The generic architecture of binary modulation scheme is shown Figure 1.

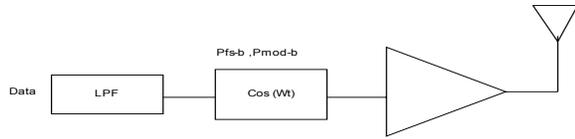


Figure 1. Binary modulation

It consists of low pass filter, frequency synthesizer. The modulation circuitry is integrated together with the frequency synthesizer. To transmit data using this architecture, the VCO can be either directly or indirectly modulated. The architecture of a radio that uses M -ary modulation is shown in Figure 2.

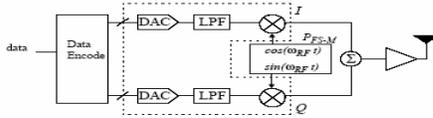


Figure 2. M-ary modulation

Here, the data encoder parallelizes serially input bits and then passes the result to a digital-to-analog converter. The analog values produced serve as output levels for the in-phase (I) and quadrature (Q) components of the output signal. The energy consumption for the binary modulation architecture can be expressed as

$$E_{bin} = (P_{mod-B} + P_{FS-B})T_{on} + P_{FS}T_{st} + P_{out-B}T_{on} \quad (1)$$

While the energy consumption for M -ary modulation is

$$E_{M-ary} = \frac{(P_{mod-M} + P_{FS-M})T_{on}}{\log_2 M} + \frac{P_{FS-M}T_{st} + P_{out-M}T_{on}}{\log_2 M} \quad (2)$$

Equations (1) and (2), P_{mod-B} and P_{mod-M} represents the power consumption of the binary and M -ary modulation circuitry, P_{FS-B} and $P_{FS@M}$ represent the power consumed by the frequency synthesizer, P_{out-B} and P_{out-M} represent the output transmit power for binary or M -ary modulation, T_{on} is the transmit on time, and T_{st} is the startup time. As mentioned, for the same number of bits, T_{on} for M -ary modulation is less than T_{on} for binary modulation. Note that $n = \log_2 M$, the number of bits per symbol. The factors of α and β can be expressed as

$$\alpha = \frac{P_{mod-M}}{P_{mod-B}} \quad (3)$$

$$\beta = \frac{P_{FS-M}}{P_{FS-B}} \quad (4)$$

Here, α represents the ratio of the power consumption of the modulation circuitry between M -ary and binary modulation, while β is the ratio of synthesizer power between the M -ary

and binary schemes. Basically these parameters represent the overhead that is added to the modulation and frequency synthesizer circuitry when one switches from a binary modulation scheme to an M -ary modulation scheme.

When we compare (1) and (2), we can see that M -ary modulation achieves lower energy consumption when the following condition is satisfied. For case of binary modulation, we assume the following energy model

$$\alpha < n \left[\frac{1 - P_{FS-B} \left\{ \left(1 - \frac{\beta}{n}\right) T_{on} + (1 - \beta) T_{st} \right\}}{P_{mod-B} T_{on}} \right] + \frac{n P_{out-B} - P_{out-M}}{P_{mod-B} - P_{mod-M}} \quad (5)$$

The last two terms of (5) can be ignored since $P_{out@B}$ and $P_{out@M}$ are negligible compared to the power of the frequency synthesizer.

2.2 Choice of modulation scheme

The choice of modulation scheme depends on several factors namely the required and desirable data rate and symbol rate, the implementation complexity the relationship between radiated power and target BER and the expected channel characteristics.

To maximize the time the transceiver can spend in sleep mode, the transmit time should be minimized. The higher the data rate offered by a transceiver/modulation, the smaller the time needed to transmit a given amount of data and, consequently the smaller energy consumption. A second observation is that the power consumption of a modulation scheme depends much more on the symbol rate than on the data rate.

The desire for high data rates at low symbol rates calls for M -ary modulation schemes. But there are trade offs:

- M -ary modulation requires more complex digital and analog circuitry than binary modulation
- Many M -ary modulation schemes require for increasing m an increase E_b/n_0 ratio consequently an increase radiated power to achieve the target BER. Others become less and less bandwidth efficient.
- In many WSN applications, the packets are short. For these packets, the start up time dominates the overall energy consumption. So, choosing m -ary modulation schemes for reducing the transmission time is irrelevant.

M	2	4	8	16	32	64
M-PSK	10.5	10.5	14.0	18.5	23.4	28.5
Eb/No						
M-FSK	13.5	10.8	9.3	8.2	7.5	6.9
Eb/No						

Table I Eb/No[db] required at the receiver to reach a BER of 10^{-6} channel for M ary orthogonal FSK and PSK

$$E_{binary} \left(\frac{E_b}{N_o} \right) = PT_{start} + \left(P_{mod} + P_{FS} + P_{tx} \left(\frac{E_b}{N_o} \right) \right) \times \left(\frac{n}{B} \right) \quad (6)$$

Where n is the number of data bits to transmit in a packet for the case of M-ary modulation, it is assumed that the power consumption of the modulator and the frequency synthesizer are increased by some factor $\alpha > 1$, $\beta > 1$, such that the over all energy expenditure is

$$E_{Mry} \frac{E_b}{N_o} B \times \lg_2 M = \beta \times P_{IS} \times T_{start} + \alpha \times P_{mod} + \beta \times P_{IS}$$

$$P_{IS} \left(\frac{E_b}{N_o} B \times \lg_2 M \right) \times \left(\frac{n}{B} \times \lg_2 M \right) \quad (7)$$

Assuming the value of $\beta=1.75$ for both FSK and PSK modulation we can evaluate the ratio $\frac{E_{Mry}}{E_{Binary}}$ to measure

the energy advantage or disadvantage of M-ary modulation over binary modulation. For large packet size M-ary FSK modulation is favorable, since the actual packet transmission time are shorten and further more E_b/N_o decreases for increasing M, at the expense of a reduced bandwidth efficiency. For M-ary PSK, only certain values of M give an energy advantage ; For larger m, the increased E_b/N_o overweigh the gain due to reduced transmit time. For small packet sizes, the binary modulation schemes are more energy efficient for both PSK and FSK, because the energy costs are dominated by the startup time.

3. Hop Distance Estimation

The fundamental problem in wireless sensor networks, how many hops does it take a packet to be relayed for a given distance. For a deterministic topology, this hop-distance estimation reduces to a simple geometry problem. However, a statistical study is needed for randomly deployed WSNs. We propose a maximum-likelihood decision based on the conditional PDF of $f(r|H_i)$. Due to the computational complexity of $f(r|H_i)$, we propose an attenuated Gaussian approximation for the conditional PDF.

3.1 Hop Distance Relation

The relation between the Euclidean distance and network distance also referred to as hop-distance relation, catches a lot of research interest recently.

The minimum ratio of the Euclidean distance to the network distance is used to estimate the number of hops,

$$r = \min_j \frac{d(i,j)}{h(i,j)} \quad (8)$$

The $\tilde{d}_{i,j}$ and $\tilde{h}_{i,j}$ are the Euclidean distance and network distance between nodes i and j, respectively. The constant value r is a good lower bound, but might not be enough to describe the nonlinear relation between Euclidean distance and network distance. In fact, their relation is often treated as linear for convenience, for example, $\lceil r/R \rceil + 1$ is widely used to estimate the needed number of hops to reach distance r given transmission range R. Against this simple intuition, the relation between Euclidean distance and network distance is far more complex. Although many analytic results are available in the Literature, computational complexity limits their applications. Therefore, we try to

approximate the hop distance relation and simplify the decision process.

3.2 Estimation of Network Distance Based on Euclidean Distance

Suppose the sensor nodes are placed on an area at random, and N^A , the number of nodes in a given area A, follows two-dimensional Poisson distribution with average density \bar{n} . The problem of interest is to find the number of hops needed to reach a distance r away. We can make a maximum likelihood (ML) decision,

$$H = \operatorname{argmax}_n f(r|H_n), \quad n = 1, 2, 3, \dots \quad (9)$$

Where the event H_n can be described as “the minimum number of hops is n from the source to the specific node at Euclidean distance r.” In the following discussion, we are trying to approximate $f(r|H_n)$ for 2D Poisson distribution.

3.2.1 Attenuated Gaussian approximation

The objective function can be approximated by

$$f(r|H_n) = \alpha^n \frac{e^{-(r-nm)^2}}{2\sigma n^2} \quad (10)$$

Where α is the equivalent attenuation base, m n and σn are the mean and standard deviation respectively.

No of Hops	1	2	3	4	5	6	7
Mean	19.991	45.132	72.01	99.45	127.14	154.96	182.68
S.D	7.0651	7.8365	8.2129	8.391	8.5323	8.6147	8.573

Table II. Statistics of $f(r|H_n)$

Since $f(r|H_n)$ attenuates with n increasing, α must be less than 1. The specific values of these parameters can be estimated from simulations or computed numerically from the exact PDFs. Our extensive simulations show that even for only moderately large H_i , $f(r|H_i)$ has the following properties.

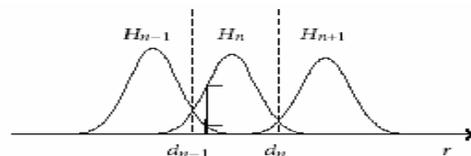


Figure 3. Gaussian Approximation

- (1) $\sigma_n \approx \sigma_{n-1}$, which means that the neighboring joint PDFs have similar spread.
- (2) $m_n - m_{n-1} \approx mn+1 - mn$, which means that the joint PDFs are evenly spaced.
- (3) $3 < (m_n - m_{n-1})/\sigma_n < 5$, which means the overlap between the neighboring joint PDFs is small but not negligible.
- (4) $(m_n - m_{n-2})/\sigma_n \gg 5$, which means the overlap between the non neighboring joint PDFs is negligible.
- (5) $\alpha < 1$. For large density λ , $\alpha \rightarrow 1$. Along with property (1), this tells us that the neighboring joint PDFs have nearly identical shape.

These properties largely simplify the decision rule and the error analysis.

3.2.2 Decision boundaries

Following property (2), and observing the $f(r | H_i)$ in Figure 3, the decision is needed only between neighboring H_i , that is,

$$f(r | H_n) \sum_{n+1}^n f(r | H_{n+1}) \quad (11)$$

This is because, for a specific value of r , there are only two values of H_i with dominating $f(r | H_i)$, compared to which $f(r | H_i)$ for other values of H_i is negligible. Substituting (6) into (8), we obtain the decision boundary d_n between the regions H_n and H_{n+1} ,

$$d_n = B + \left(\frac{\sqrt{B \times B + (A \times C)}}{A} \right) \quad (12)$$

Where, $A = \sigma_{(n+1)^2} - \sigma_{(n)^2}$;

$B = m_n \sigma_{(n+1)^2} - m_{n+1} \sigma_{(n)^2}$ and

$C = m_{(n)^2} \sigma_{(n+1)^2} - m_{(n+1)^2} \sigma_{(n)^2} + 2\sigma_{(n)^2} \sigma_{(n+1)^2} \ln \alpha$

Using property (1),

$$d_n = \frac{m_{(n+1)^2} - m_{(n)^2} - 2\sigma_{(n)^2} \ln \alpha}{2(m_{n+1} - m_n)}$$

For large density λ , property (5) is applicable, (9) simplifies to

$$d_n = \frac{\sigma_{(n)^2} M_{(n+1)^2} + \sigma_{(n+1)^2} M_n}{\sigma_n + \sigma_{2n+1}}$$

Applying property (1) to (11),

$$d_n = \frac{m_n + M_{n+1}}{2}$$

No matter which approximate solution we choose for d_n , the decision rule is given by

$$d_{n-1} < r \leq d_n, \text{ we decide } n, \text{ if } d_{n-1} < r < d_n \quad (13)$$

3.3 Application Examples

We provide two application examples, latency and energy estimation, in this section. To emphasize the role of the number of hops in the estimation, we use general time and energy models. On how to derive the parameters such as T_{rx} , T_{tx} for a specific routing scheme

3.3.1 Latency estimation

We use a simple time model, in which the latency increases linearly with the number of hops. Suppose it takes T_{rx} , T_{tx} for a sensor node to process 1 bit of incoming and outgoing messages, respectively, and T_{pr} is the required time to transmit 1 bit of message through a band-limited channel. Therefore, the latency introduced for each hop is

$$T_{hop} = T_{tx} + T_{pr} + T_{rx} \quad (14)$$

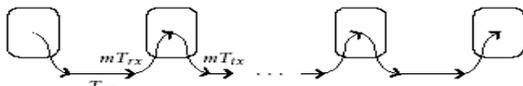


Figure 4. Time Model

Name	Value
r_0	86.2 m
E_{elec}	50 nJ/bit
E_{DA}	5 nJ/bit
ϵ_{fs}	10 pJ/bit/m ²
ϵ_{mp}	0.0013 pJ/bit/m ⁴

Table III. Energy Consumption Parameters

As shown in Figure 4, given the end-to-end distance r , we can find the required number of hops according to (13), thus, a good estimator of the total latency of an l-bit message is given by

$$ln T_{hop} \quad (15)$$

3.3.2 Energy consumption estimation

The following model is adopted from [2] where perfect power control is assumed. To transmit l bits over distance r , the sender's radio expends

$$E_{tx}(l, r) = lE_{elec} + \epsilon_{fs} r^2, r < d_0 \quad (16)$$

$$= lE_{elec} + \epsilon_{mp} r^4, r < d_0$$

and the receiver's radio expends

$$E_{rx}(l, r) = lE_{elec} \quad (17)$$

E_{elec} is the unit energy consumed by the electronics to process one bit of message, ϵ_{fs} and ϵ_{mp} are the amplifier factor for free-space and multipath models, respectively, and d_0 is the reference distance to determine which model to use. In fact, the first branch of (15) assumes free-space propagation and the second branch uses a path-loss exponent of 4. The values of these communication energy parameters are set as in Table 5.2. Let s_n denote the single-hop distance from the n th hop to the n th-hop. Obviously, $s_n \leq R$. In our experimental setting, $R = 45m < d_0$ so that the free-space model is always used. This agrees well with most applications, in which multi hop short-range transmission is preferred to avoid the exponential increase in energy consumption for long-range transmission. Naturally, the end-to-end energy consumption for sending l bit over distance r is given by (18)

$$E_{total}(l, r) = \sum E_{tx}(l, r_1) + E_{rx}(l) \quad (18)$$

$$E_{total}(l, r) = \sum E_{tx}(l, r) + E_{rx}(l)$$

Where n is the estimated number of hops for given r and r_1 is the single-hop distance because the message is relayed hop by hop. On the average,

$$E_{total}(l, r) = nl \left(2E_{elec} + \epsilon_{fs} (m_1^2 + \sigma_1^2) \right) \quad (19)$$

The energy consumption parameters are shown in Table 3.

[3] 4. Simulation Results

The simulation results have been obtained using the quantitative analysis. NS-2 has been used to simulate the results. The energy consumption of wireless sensor node for hop distance and various modulation schemes is being compared and the results are shown.

Figure 5 shows the sample network consisting of randomly deployed nodes is generated for $N=45$ nodes each with a transmission range $R=45$ m. The number of hops is estimated for each node using (13) and (20), and then the latency and energy consumption are estimated using (15) and (19), respectively. As comparison to our proposed statistic-based estimator, we choose a widely used linear estimator, Linear estimator 1

$$n = \left\lceil \frac{r}{R} \right\rceil + 1 \quad (20)$$

Linear estimator 2

$$n = \left\lceil \frac{r}{R} \right\rceil + 2 \quad (21)$$

Where, r is the given distance, R , the transmission range, and $\lceil r/R \rceil$ is the maximum integer less than r/R . We plot the average of energy consumption and latency in Figures 6 and 7. The latency is plotted in units of T_{hop} while the energy consumption in units of joules. The linear estimators, no matter what value their parameters take, may significantly underestimate or overestimate the latency and energy consumption, while our statistic based model keeps close to the actual latency and energy consumption at all ranges except for the border.

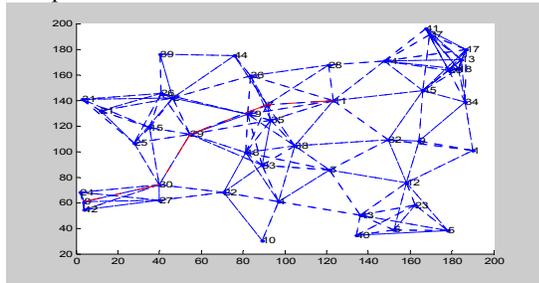


Figure 5. Randomly generated network with 45 nodes

4.1 Hop Distance and Energy

The figure 6 describes the energy consumption of the sensor node with respect to the end to end distance. From the graph it can be said that as the network distance increases the energy consumed by the node also increases. It is so because when the node distance is increased the number of hop increases i.e. the transmitting and processing power increases proportionally. The energy for the given hop distance is determined by both probabilistic and statistical methods

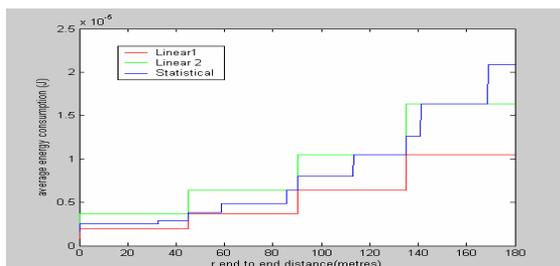


Figure 6. Hop Distance Energy Estimation

4.2 Latency Estimation

The figure 7 describes the latency of the sensor node with respect to the end to end distance. From the graph it can be said that as the network distance increases the latency also increases. Latency increases linearly with the number of hops. The number of hops is calculated from the network distance.

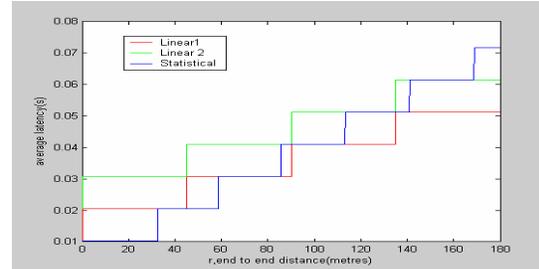


Figure 7. Latency Estimation

4.3 Comparison of Binary and M-Ary Modulation in terms of Energy

A comparison of the energy consumption of binary modulation and M -ary modulation is shown in Figure 8. In the figure, infers that the ratio of the energy consumption of M -ary modulation to the energy consumption of binary modulation is plotted versus the overhead α . We vary M to produce different M -ary modulation schemes. For each scheme, we also vary the startup time and assume that 100 bit packets are sent at 1 Mbps. This implies that in M -ary scheme, $l = \log M$ mega symbols are sent per second and the on time is decreased. As expected, the M -ary modulation scheme achieves the lowest energy when the overhead α is small and T_{st} is about $50\mu s$. When the startup time is about $200\mu s$, however, the energy consumption is higher for M -ary modulation regardless of α . This is because the energy consumption due to startup time dominates the energy consumption due to transmit on-time. Hence, reducing T_{on} by using a larger M has a negligible effect on the total energy consumption.

The ratio of the energy consumed by M -ary modulation to the energy consumed by binary modulation is plotted versus, the ratio of the modulation circuitry power consumption.

From the plot it can be observed that M -ary modulation scheme achieves the lowest energy when the overhead α is small and T_{st} is about $50\mu s$. When the startup time is about $200\mu s$, however, the energy consumption is higher for M -ary modulation regardless of α .

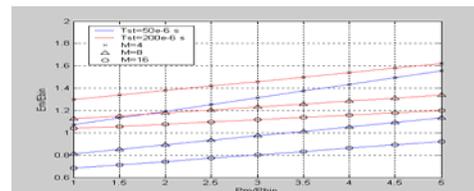


Figure 8. Comparison of Binary and M-ary modulation in terms of Energy

4.4 Comparison of MFSK and MPSK in terms of Energy

The figure 9 shows the energy consumed by M -ary orthogonal PSK and FSK in comparison with binary modulation. Assuming the value of $\beta=1.75$ for both FSK and

PSK modulation we can evaluate the ratio $E_{\text{binary}} / E_{\text{M-ary}}$ to measure the performance of M-ary modulation over binary modulation.

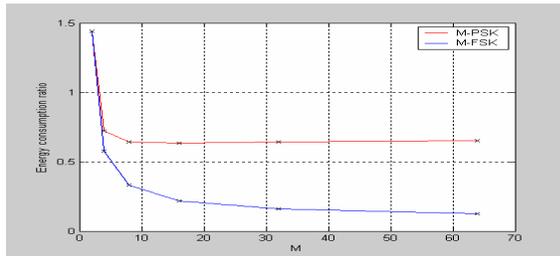


Figure 9. Comparison of MFSK and MPSK in terms of Energy

[4] 5. Conclusion and Future work

The performance of binary and M-ary modulation schemes in terms of their energy consumption are compared. For large packet size M-ary FSK modulation is favorable. For M-ary PSK, only certain values of M give an energy advantage; For larger M, the increased E_b/N_0 outweighs the gain due to reduced transmit time. For small packet sizes, the binary modulation schemes are more energy efficient for both PSK and FSK, because the energy costs are dominated by the startup time. We have shown that reducing the startup time of the node reduces energy consumption for M-ary QAM.

The statistical based method for estimating the number of hops for relaying a packet to a distance r is proposed. This method is efficient compared to the widely used linear estimators and more accurately predicts the number of hops.

The future works to be carried out in this project are, to determine the performance of various coding techniques and other adaptive modulation schemes used in the Physical layer of the wireless sensor networks. The statistical method for estimating the number of hops is proposed under the assumption that sensor nodes are stationary. The mobility parameter must be included to achieve more accurate and realistic method for practical applications where mobility is of major concern.

[5] References

- [1] Eugene Shih, SeongHwan Cho, Nathan Ickes, Rex Min, Amit Sinha, Alice Wang, Anantha

Chandrakasan, "Physical layer driven protocol and algorithm design for energy efficient wireless sensor networks", Proc. MOBICOM, 2001, pp. 272–287.

- [2] Heinzelman, W.B. Chandrakasan, A.P. Balakrishnan, H. "An application-specific protocol architecture for wireless microsensor networks", IEEE Transactions on Wireless Communications, Oct 2002, pp. 660- 670.
- [3] Tang, Q.; Yang, L.; Giannakis, G.B.; Qin, T. "Battery Power Efficiency of PPM and FSK in Wireless Sensor Networks ", IEEE Transactions on Wireless Communications, April 2007, pp.1308 – 1319.
- [4] Akyildiz I.F., Weilian Su, Sankarasubramaniam Y. and Cayirci E. (2002), 'A survey on sensor networks', IEEE Communications Magazine, Vol. 40, Issue 8, pp. 102-114.
- [5] Holger Karl, Andreas Willig, "Protocols and Architectures for Wireless Sensor Networks", published by John Wiley and Sons, 2005, pp.85-109
- [6] S. Cui, A. J. Goldsmith and A. Bahai, "Energy-Constrained Modulation Optimization," IEEE Trans. on Wireless Comm., 2005
- [7] E. Ekici, S. Vural, J. McNair, D. Al-Abri "Secure probabilistic location verification in randomly deployed wireless sensor networks " Elsevier Science Publishers B. V, April 2006, pp.,195-209
- [8] Wang A., Heinzelman W. and Chandrakasan A., 'Energy-scalable protocols for battery-operated microsensor networks', Proc. 1999IEEE Workshop Signal Processing Systems (SiPS '99), pp. 483–492
- [9] Wenliang Du, Lei Fang, Ning Peng "LAD: localization anomaly detection for wireless sensor networks" 19th International parallel and distributed processing symposium, July 2006, pp. 874 – 886
- [10] Amitabh Basu, Jie Gao, Joseph S. B. Mitchell, Girishkumar Sabhnani, "Distributed localization using noisy distance and angle information" 7th ACM international symposium on Mobile ad hoc networking and computing, 2006, pp. 262 – 273
- [11] N. B. Priyantha, H. Balakrishnan, E. D. Demaine, and S. Teller, "Mobile-assisted localization in wireless sensor networks," in Proceedings of the 24th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM'05), vol.1, pp. 172–183, Miami, Fla, USA, March 2005.