Implementation of estimation algorithms in wireless sensor networks

Pavlidis Charilaos

A thesis submitted in partial fulfillment for my
diploma of Computer, Telecommunications and Nets Engineering

University of Thessaly

Supervisors:
Prof. Argyriou Antonios
Prof. Athanasios Korakis

October 2015

Περίληψη

Η διπλωματική αυτή αποσκοπεί στην έρευνα για μείωση της ενέργειας ενώς δικτύου ασύρματων αισθητήρων, με πειραματισμό στον αριθμό των βιτ που χρησιμοποιούνται κατά την διάρκεια κβαντοποίησης του σήματος. Οι βασικές διεργασίες κάθε αισθητήρα σε ένα τέτοιο δίκτυο είναι η δειγματοληψία του φαινομένου, η μετατροπή του αναλογικού σήματος σε ψηφιακό και έπειτα η αποστολή του σήματος στο κέντρο ελέγχου. Το κέντρο ελέγχου θεωρούμε ότι συλλέγει τα δεδομένα από τους αισθητήρες και κάνει μια εκτίμηση του αρχικού σήματος με την μέθοδο weighted least square, προσπαθώντας να μειώσει την κατανάλωση ενέργειας. Στην προσπάθεια αυτή, δημιουργούμε ένα πρόβλημα αποτελούμενο από την συνάρτιση μείωσης της ενέργειας η οποία περιορίζεται από το μοντέλο παραμόρφωσης του σήματος μέσο του σφάλματος ελαχίστων τετραγώννων. Το δίκτυο ασύρματων αισθητήρων λειτουργεί με βάση το πρωτόκολο sub-1GHz IEEE 802.11ah MAC/PHY και τα αποτελέσματα που προκύπτουν μπορούν να χρησιμοποιηθούν στην πράξη.

Abstract

In this thesis we research the effect of bit's number during quantization on the power consumption of a wireless sensor network (WSN). We assume that in our WSN each sensor makes observations, converts them from analog to digital and transmits them to a fusion center (FC). The FC collects these data and makes an estimation with the linear weighted least square (WLS) algorithm to identify the observations with minor power consumption. We consider a power minimization object function constrained by MSE distortion model correspond it to a mixed integer nonlinear program (MINLP). The WSN operates under the sub-1GHz IEEE 802.11ah MAC/PHY standards and our outcomes could be useful for it.

Acknowledgements

I want to thank my supervisor prof. A. Argyriou for introducing me the subject of my thesis and his valuable guidance on each step of its implementation.

I want to thank my family and friends for their especial and indispensable support on the years of my studies.

Contents

Chapter 1

Theoretical Framework

1.1 Introduction

In recent years, wireless sensor networks (WSN) present a high interest research field, since their implementation increases steadily. The process in general is as follows: sensors measure a quantity of interest which corresponds to an analog signal, transform it to digital and transmit it wireless to the fusion center (FC) for additional processing and eventually to estimate the desire signal. Some of the areas where WSNs have implementation are weather forecast (e.g. temperature measurements), medical (e.g. heartbeats measurements), safety systems for fire detection (e.g. detecting presence of smoke) and generally to Internet of Things (IoT) or applications.

To begin with, possibly the parameter which plays the most significant role in the function of a WSN is power consumption, specifically when we have a significant number of sensors or currently where the application of WSNs is on augmentation. For that reason, trying to minimize the power consumption became a high interest as well. Nevertheless, the power is promptly related with the accuracy of the estimation since lower power transmission increase the probability of packet loss. This point is what motivates this paper and consequently to analyze in detail the operation of a WSN. Power optimization based on the different features of a WSN and especially on the IEEE 802.11ah standard like we do so, will bring about further development on this standard and to the wider technology of WSNs.

Each sensor makes observations (sampling procedure) to obtain an analog signal. To transmit this signal, it is necessary to quantize it. For quantization, we have to select the number of bits that will be used. If we consider that these values will be sent to the FC and that the number of the bits controls the size of each measurement (thus the quality), we conclude that this number will play a significant role in our system. After conversion the values will be packed and sent under a path loss channel to the FC. When the FC receives the values it is time to make an estimation for these data. In addition, we assume that our data is uncorrelated and we cannot use smart techniques for correlated data estimation which decrease the estimation error. We approach the problem with a linear weighted least square (WLS) algorithm, trying to have an acceptable mean square error (MSE). It is clear that the MSE is affected by the quality and the number of the received observations, which have to deal with the number of bits per sample. However, the path loss channel we assumed before has a significant effect on measurements' quality as well. Good quality of observations makes the estimation easier but each sensor will send fewer observations. Summarizing, we combine all the above to find an ideal trade-off for the bits of quantization and power consumption.

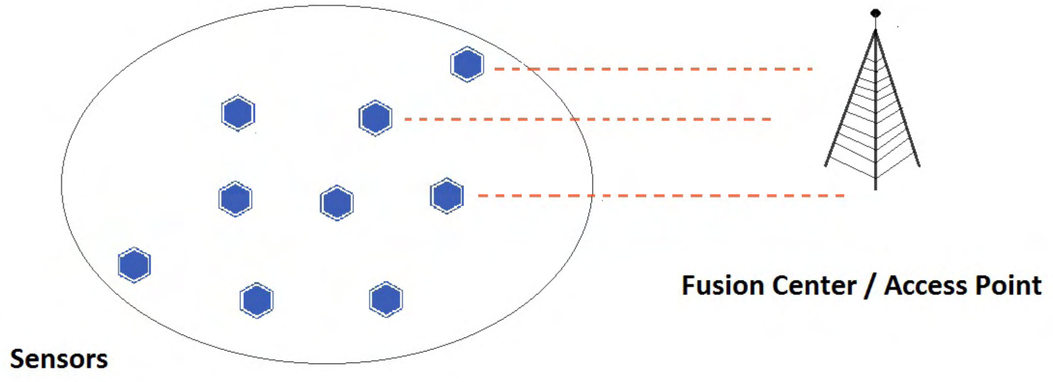


Figure 1.1: The figure indicates our system model where the nodes are randomly distributed in a specific area. The data are transmitted after sampling using the IEEE 802.11ah MAC to contend for channel access.

Related Work. Several researchers have investigated problems related to power consumption of WSNs. Nevertheless, all of them differ in terms of the approach they followed. In [3] the author considered a path loss channel with a mean value and calculates the number of the observation which arrives to the FC by the outage probability, however, the randomness of the channel gain is not taking into account. In addition, a relay node is involved . In [4] the authors consider analog signal for transmission and they incorporate a correlated data case, where smart practices can be used for greater estimation.

We present a scenario where the data among the sensors are uncorrelated and there is no presence of any relay. Moreover, we consider the randomness of the channel gain throughout each communication round and the bit error rate (BER) of the received data on the FC. Hopefully, to make our effort more realistic with practicality.

1.2 System Model

The observations from each sensor are modeled with a vector $\theta_i = [\theta_1 \dots \theta_k]$. Note that data among sensors are uncorrelated because the sensors are located at large physical distances [3].

Each sensor collects several observations (samples) during a period of T seconds that depends on the monitored phenomenon [3]. Because of the AWGN sampling noise, the signal takes the form $s_i = \theta_i + z_i$ with $z_i \sim N(0, \sigma_{z_i}^2)$ and this is the signal which is led to quantizer. After quantizing we have this signal:

$$y_i = \theta_i + z_i + q_i \tag{1.1}$$

Quantization adds noise q_i on each sensor independently, similar to the sampling noise.

For a quantization with $\overline{R_i}$ bits/sample, the variance of the quantization noise (or the distortion), under the use of a uniform probabilistic quantizer $Q(\cdot)$ [5] at each sensor is :

$$\sigma_{q_i}^2 = \frac{A^2}{(2^{\overline{R_i}} + 1)^2} \tag{1.2}$$

and A is the amplitude of the initial analog signal.

Sensors collects a number of observations K ($K\overline{R_i}$ bits). Depending on the used MCS, we have a number of bits R_i bits/symbol parts to it. This parameter takes into account the use of a capacity-achieving AWGN code and the mapping of the quantized digital samples to digital baseband symbols after channel coding and digital modulation, is denoted as follows [3]:

$$x_{d_i} = CC - PSK(y_i) \tag{1.3}$$

We assume a flat quasi-static Rayleigh fading channel with a gain factor h. Similarly, Pi is the transmitted power at sensor i. Considering that x_{d_i} is the signal lead to transmission we take:

$$y_{i,f_c} = \sqrt{P_i} h_{i,f_c} x_{d_i} + w_{f_c} \tag{1.4}$$

where $w_{f_c} \sim N(0, \sigma^2)$ is the AWGN caused of the signal transmission.

IEEE 802.11ah. To transmit the digital packet to the FC each node must access the channel. It does so with the IEEE 802.11ah [2], for which we model its core PHY/MAC functionalities in our overall system model. Regarding the 802.11ah PHY features, it uses the lower MCSs of IEEE 802.11ac. BPSK with code rate $\frac{1}{2}$ was adopted to ensure long range and this was the selected to be the value for Ri [3]. At the MAC the standard uses the distributed coordination function (DCF) for contenting for channel access [2].

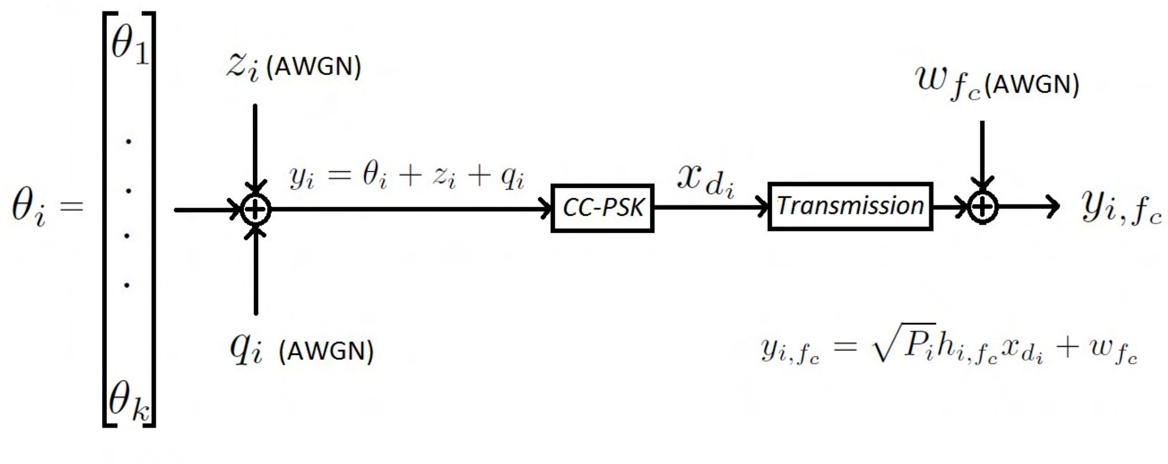


Figure 1.2: The figure shows our "mathematical" system model described in section II.

1.3 Distortion and Other Parameters

1.3.1 Signal to Noise Ratio and Bit Error Rate

Signal to noise ratio (SNR) is the power of the signal over the power of the noise. We control this ratio in our effort to transmit successfully. This is the first constraint for our system and there will be a threshold to obtain a specified SNR.

Another interesting ratio for our scope is bit error rate (BER) which is the proportion of the number of wrong bits we finally receive to the FC over the total number of received bits. We use this parameter for identifying the number of the correct observations we receive. The number of observations is calculated below and it is included in the second constraint of our system.

It is quite evident, that any system where the power of the signal or bits distortion are involved, aims to high SNR and low BER for achieving undistorted and correct data. High SNR indicates that a signal is powerful compared with the power of noise, thus it arrives to its destination with the absent of distortion and without incorrectly bits, which corresponds to low BER. It is obvious that SNR and BER are inversely quantities and in our attempt BER is calculated using SNR.

1.3.2 MSE and System Constraints

As we have already mentioned we will try to estimate the data sent from each sensor to the FC. For a start we will try to estimate the transmitted data from equation (4) which has to do with the transmission of the signal. Mind that these are the data for decoding. By WLS we take [1]:

$$\hat{y_i} = (c^H \Sigma_{v_i} c)^{-1} c^H {\Sigma_{v_i}}^{-1} y_i \tag{1.5}$$

where Σ_{v_i} is the autocorrelation matrix. Point out that this matrix is diagonal and zero elsewhere. Because both equations (1) and (4) have not got dependent elements and all the noise factors is Gaussian.

The accuracy of each estimator can be measured using the MSE variable. To calculate MSE we have to calculate the error covariance matrix and from [1] we take:

$$\Sigma_{e,i} = (c^H \Sigma_{v_i} c)^{-1} \tag{1.6}$$

$\Sigma_{e,i}$ is also diagonal and we can proof that each element of the diagonal is:

$$[\Sigma_{e,i}]_{i,i} = \frac{\sigma^2}{P_i h_{i,f_c}^2} \tag{1.7}$$

where $\frac{\sigma^2}{P_i h_{i,f_c}^2}$ is equal to $1/SNR$ and we will constraint it to have an acceptable distortion of our signal.

The second constraint of our model derives from applying the above process to the equation (1). The elements of the diagonal error's covariance matrix, alike equation (12) in [3] is :

$$MSE(i) = \frac{\sigma_{z_i}^2 + \sigma_{q_i}^2}{M_{rec}(i)} \tag{1.8}$$

where $M_{rec}(i)$ is the number of the correct observations received to the FC and we model it in the next subsection.

Note that the number of bits per observation $\overline{R_i}$ has a significant impact on the MSE. If we choose to quantize our signal with little bits, the sensor will send a lot of observations which decreases the MSE, however, it is possible that these observations do not correspond to the original, because during the procedure of quantization the analog signal has been digitalized with few bits, thus significant information may have been lost. On the other hand, if we process the signal with a big number of bits, the quality of the observations will be significant, although, provided that the transmission bits are constant, it will be sent a little number of observations and the MSE will be increased. Therefore, a trade-off has to be found for satisfy both cases.

1.3.3 Number of Observations

We have already said that BER will play significant role to our system model. Likewise, each observation is constituted by a number of bits depending on the number chosen during quantization R_i. One incorrect bit is enough to make the observation false and useless. Knowing the proportional of the wrong bits over the correct bits (BER), we can find the number of the false bits we have in a codeword. Now, if we consider that the wrong bits is uniformly and remotely to one another distributed in the codeword , we can conclude that the number of wrong bits is $BER\overline{R_i}$. Note that if there are wrong bits beside to one another, it is likely to have more than one wrong bit in an observation, thus less than $BER\overline{R_i}$ useless bits. However, the distribution we mentioned before is the worst scenario and we proceed with that. Another parameter we need for the number of observations is throughput. A sensor operating under the DCF mode in IEEE 802.11ah will share the channel with the remaining nodes [3]. Based in the throughput model in [6] we have $S^{DCF}(K, R_i, T, N)$ where R_i is the bits per symbol MCS uses, K is the number of packets produces every period T and N is the number of nodes. This model considers only the impact of collisions in the throughput [3].What we do is to take into account the distortion of the signal, caused during transmission. We can present know the observations' number:

$$M_{rec}(i) = S^{DCF}(K, R_i, T, N)(1 - BER * \overline{R_i})\frac{T}{\overline{R_i}} \tag{1.9}$$

where $(1 - BER * \overline{R_i})$ is the proportion of the correct bits, multiplied by the period T which the data are produced and finally divide all these bits by $\overline{R_i}$ which the bits per sample.

Alternative-Theoretical Model.The above formula is a variation of the equation (7) in [3] where the outage probability P_{out} is enrolled instead of BER. P_{out} indicates the failure probability of the data to be transmitted on the FC and the only difference is that $(1 - BER * \overline{R_i})$ is substituted by $(1 - P_{out})$. Additionally, we present a comparison of these two methods to find out the derived differences on power consumption providing that our model refers to a random gain channel, whereas the $('P'_{out}$ model to the mean value of the channel which render it to the theoretical estimation.

1.4 The Power Optimization Problem

Our attempt is characterized by an object function and its goal is to minimize the power consumption on each sensor. We are trying to reach an optimization solution taking into consideration the two constrains presented on previous section. The presence of these two constraints, exist to ensure an acceptable quality to the received data. D_{tr} is the threshold for the acceptable distortion caused by transmission and D_{sq} is the equivalent caused by sampling and quantization. $\mathbf{P} = [P_1 \dots P_n]$ is the vector for the power consumption on each sensor i which is also constrained $\{\forall i P_i \leq P^{MAX}\}$. We approach the optimal solution by experimentation on the values of the vector **P** and the number of bits per sample $\overline{R_i}$. Eventually, the emerging form is;

$$\min_{\mathbf{P}, \overline{R_i}} \sum_{i=1}^{N} P_i$$

$$s.t. \qquad \frac{1}{SNR} \leq D_{tr} \tag{1.10}$$

$$and \qquad \sum_{i=1}^{N} \overline{R_i} \frac{(\sigma_z^2 + \frac{A^2}{(2^{R_i}+1)^2})}{S^{DCF}(K, R_i, T, N)(1 - BER\overline{R_i})T} \leq D_{sq} \tag{1.11}$$

Point out that $\overline{R_i}$ looks to has a significant impact on (1.11) and this is what we try to find out.

Chapter 2

Simulation and Conclusion

2.1 Simulation Results

[The graphs are shown after Conclusion section]

The simulation parameters were set as described below. The variances involved we set $\sigma^2 = 10^{-3}$ and $\sigma_z^2 = 10^{-3}$, the amplitude of quantization $A = 1$,the throughput assumed to be constant $S^{DCF} = 100kbps$ and the sampling period $T = 1s$. The two thresholds for transmission and sampling-quantizing are set to $D_{sq} = 0.5$ and $D_{tr} = 10^{-6}$, while the allowable maximum power $P_{MAX} = 10$. We present results for vector **P** and the number of bits per sample $\overline{R_i}$. The BPSK modulation uses 1 bits per symbol, $R_i = 1$, and a coding rate of $\frac{1}{2}$. BER is calculated using the coding rate, the $erfc(\cdot)$ function and the SNR, more specifically $BER = \frac{1}{2}erfc(\sqrt{\frac{SNR}{2}})$.

To begin with, figure (a) illustrates the range of the acceptable bits per sample which can be used for quantization, under a specific average channel gain. Equivalent, that there is an upper and a lower bound for the quantization's bits and using a value out of these bounds the problem cannot be solved. Which means that we have not got accurate estimation. It is obvious, that once the sampling-quantization threshold increases the range is increased. This performance is reasonable because greatest sampling-quantization threshold denotes that our system is able to accept lower quality observations and consequently fewer bits can be matched to an observation. Furthermore, highest threshold indicates that fewer observations can be accepted, then more bits can be used for a sample. Eventually, we can conclude that there is an optimized value (6 bits/sample), which may derives from the fact that this value guarantees the need for a big number of observations which are of high quality too. Otherwise, the result will be either a lower number of observations with high quality or the samples will have poor quality and the number of them will be significant. However, both cases have disadvantages, for the former such a high quality is not necessary and for the latter may fewer samples can be acceptable as well.

In figure (b) we make a comparison of our system with the theoretical one in [3]. The system in [3], as we described above, calculates the number of observations using the outage probability instead of BER in our approach. In addition, channel's randomness is not taking into account and the outage probability is calculated using only the average channel gain. The problem formulation in this paper is novel since it includes the BER for counting the observations and the other one the outage probability. Thus we assume that the former system is more specific because it focuses to the received packet may be or codeword at the FC, while the latter to the failure arrival of the packet may be or codeword. Besides, on our try we include the randomness of the channel gain. This figure presents the percentage (Fail Rate) which our system demands extra power compared to the theoretical outcome, for different means and variances of the channel gain. When the problem is not solved, accounting as a failure, it means that the desired MSE cannot be guaranteed for a specific random channel, however, it can be guaranteed for the theoretical one, which uses the mean value of the channel. For instance, throughout a round of communication, it is possible that the sensors will achieve a channel gain pretty worst compared with the average channel gain. Consequently, the power consumption calculated for the mean value, the theoretical outcome, will not be enough for the "worst" channel and we characterize this case as a failure. Finally, it is quite evident, that both two models present to have different power consumptions and fail rate takes notable prices, which means that channel's randomness is a significant parameter.

Figure (c) depicts two graphs where the impact of the first constraint on power consumption is examined under a specified average channel gain ($E[h^2] = 0.01$). The upper graph shows the curves for low threshold values and the lower graph for high threshold values. Definitely, as the SNR demand is getting higher (low thresholds) the power consumption increases as well. However, the curves for each threshold show that the power consumption has not got significant fluctuations among different bits, indicating that the second constraint is satisfied because high SNR corresponds to a low BER. Furthermore, we can conclude that when the BER reaches values very close to zero, it is needless to demand higher SNR because the distortion of the transmitted data will not be effected and the only result will be higher power consumption. In contrast, for high thresholds (low SNR demand) the curves has significant variances among different number of bits but they are overlapped, which means that the SNR constraint does not effects our system. In general, the first constraint (1.10) give us the ability to define the SNR value.

Graph (d) illustrates the power consumption variance among different quantization bit number over the optimized value chosen, for different average channel gains and sampling-quantizing thresholds. It is quite evident, that the rate is getting higher when the average channel gain decreases and the sampling-quantizing threshold increases. Thus, when the average channel gain is low or our system constraints are tolerant, the right selection of bits' number is necessary.

On topside of figure (e) is examined the power consumption for different throughput values and below for different periods. Notice, that both 2 graphs have the same look for relative values, for example $T = 1.3s$ and $S_{DCF} = 130kbps$ etc. , because both of them has the same impact on the denominator of (1.11). Throughput increase, means that more data or observations can be transmitted from the sensors to FC, thus the estimation will be done with greater observations and it will be more accurate. As well, further data for transmission, consequent less competitiveness among sensors, which means less power consumption for data transmission. For period, we can conclude that while the period is getting higher, each sensor communicates with the FC more rarely than it used to, hence the power consumption is decreased.

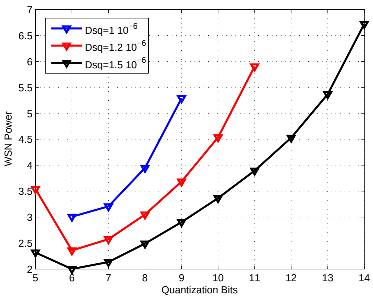
In graph (f) it is evident the average number of bits selected with the proposed estimation algorithm for optimizing the power consumption. We can say that while the variance of the channel gain increases, our algorithm demands greater quality on each observation rather a big number of observations. Considering that our throughput is constant, if the algorithm selects a big number of bits for quantization, it consequences fewer observations for transmission in the channel. However, the results using the theoretical algorithm are stable for all variances and the average channel gain shown in the graph.

Graph (g) shows the power consumption of a specified average channel gain, considering the randomness of the channel and different population nodes. There is also presented the results that the algorithm in [3] gives. It is obvious, that the theoretical approach does not match with the one proposed here, because it does not take into account channel's randomness. Furthermore, we can see that the theoretical algorithm, sometimes estimates more and sometimes less power than the proposed algorithm. This means that if we use the theoretical algorithm there will be cases that we spend more power than our system demands (for the former) and sometimes the power estimated is not enough for our system's needs (for the latter). Additionally, while the population of our sensors increases the power performance of our system looks to increase linearly, instead of the theoretical one which increases exponentially. Eventually, it is shown that while the randomness of our channel gain increases the power of our system decreases and the pace of reduction is greater for higher number of nodes.

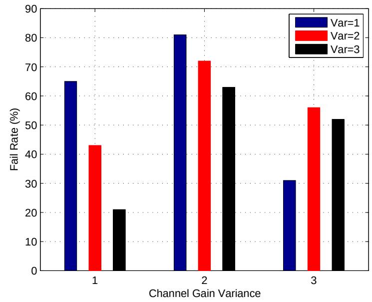
Graph (h) illustrates the fail rate introduced above for different number of nodes. It is evident, that except of the case where the average channel gain is 1 and the performance of fail rate is not stable, we have an increase of the fail rate while the population and the average channel gain is getting higher. Besides, thinking of the graph's (g) concludes where we said that the power consumption will be either unneeded or lacking for our system's needs, we can infer that if we subtract each fail rate from 100 we have the rate where the system needs less power than the estimated in the theoretical approach, which is the opposite of the fail rate.

2.2 Conclusion

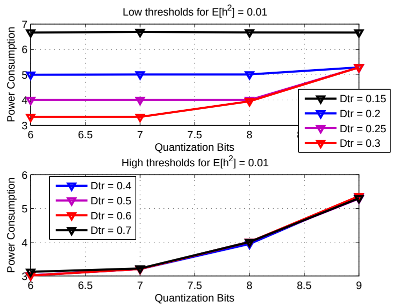
In this paper, we present an optimization problem for minimizing the power consumption of an IEEE 802.11ah WSN which focuses on the bits' number using during quantization. We attempt to estimate the measure data of the sensors with power efficiency and considering the randomness of the channel gain throughout each communication round of the sensors with the fusion center. The estimation is based on the WLS algorithm and the accuracy is succeed using the MSE. The simulation results, indicate that the number of the quantization bits has a great impact on the power consumption of the WSN and a specified value can be chosen for the individual average channel gains. Furthermore, another important factor which has a significant impact on power consumption and makes our attempt more realistic is the randomness of the channel gain.



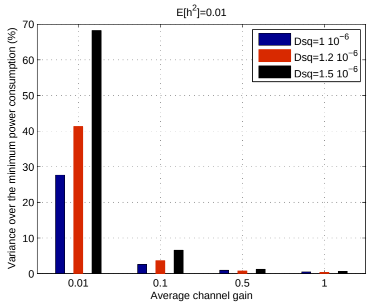
(a) Acceptable bit range



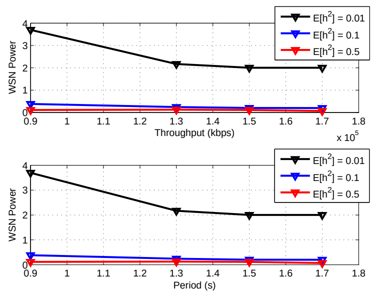
(b) Fail rate different average channel gains and variances



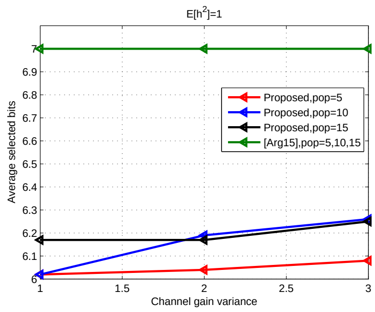
(c) High and low thresholds results for (1.11) constraint



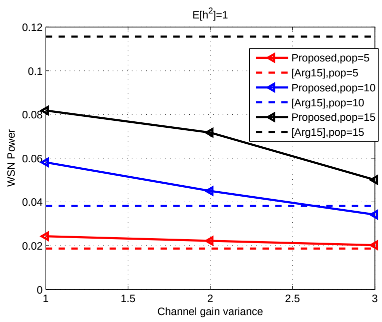
(d) Variance of power consumption over the optimized value



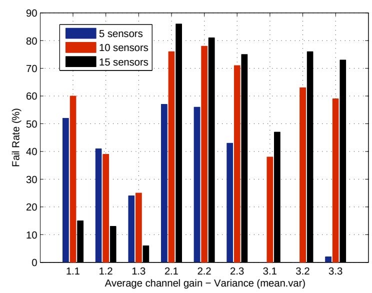
(e) Results for different throughput and period values



(f) Average number of bit selection for optimization



(g) Power consumptions for different variances and population of sensors



(h) Fail rate for different population of sensors

Figure 2.1: Results Graphs

Bibliography

[1] S. M. Kay, *Fundamentals of Statistical Signal Processing, Volume I:Estimation Theory.* Prentice Hall, 1993.

[2] http://www.ieee802.org/11/Reports/tgah update.html

[3] A. Argyriou *"Power-Efficient Estimation in IEEE 802.11ah Wireless Sensor Networks with a Cooperative Relay."*

[4] B. Israfil,K.k. Amir *"Linear Estimation of Correlated Data in Wireless Sensor Networks with Optimum Power Allocation and Analog Modulation"*, IEEE Transactions on Communications, VOL. 56, NO. 7, Jul 2008.

[5] J.-J. Xiao, S. Cui, Z.-Q. Luo, and A. Goldsmith, *Joint estimation in sensor networks under energy constraints,* in SECON, 2004.

[6] D. Malone, K. Duffy, and D. Leith, *"Modeling the 802.11 distributed coordination function in nonsaturated heterogeneous conditions," Networking*, IEEE/ACM Transactions on, vol. 15, no. 1, pp. 159–172, Feb 2007.