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Power Aware Control of an Environmental Sensor Network

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Contents

Chapter 1 Abstract

Sensor Networks are rapidly being used for several different types of monitoring and controlling applications. One of the most important issues with sensor network used in the environment is power. Among other activities sampling and transmission consume the most power while in operation. In this paper a novel technique is proposed to reduce power consumption of the network nodes without significantly affecting the data quality in the user end utilizing collaboration among sensors and modeling of the environmental data. The techniques were verified using simulations on data collected through a deployment of weather stations known as SensorSope.

Chapter 2 Introduction

THE advent of sensor networks in several monitoring and controlling applications have brought new challenges to the engineers. The most important issue is power consumption. Sensor networks are especially suited for monitoring applications because of their portability and ease of deployment. Comes with these is the low cost and maintenance requirement of such devices.

2.1 Wireless Sensor Network

Wireless Sensor Network (WSN) refers to a network of sensors connected via wireless medium. WSN is very feature rich which makes it attractive for environment monitoring applications. The main features of Wireless Sensor Networks are as follows,

- Small size nodes – easily deployable
- Low cost – can be deployed in large numbers
- Ability to communicate over the radio link – facilitates remote deployment

All of the above stated properties make wireless sensor networks to be the preferred platform for environmental monitoring applications.

On the downside of the WSN is the limited power supply to the nodes. Particularly in case of remote deployment it becomes a very dominant problem since access to the deployment is limited and long life is one of the primary requirements of such applications.

2.2 Environmental Monitoring

The nature of environmental monitoring applications requires the sensor network to be able to be active for a long duration without requirement for manual interventions. To be able to achieve this, the sensor nodes must consume very low power and/or have some sort of limitless power supply. Also the nodes need to be able to communicate to the base station as and when required. This is especially required if the network is being used to monitor critical events.

2.3 WSN Power Consumption

Given the benefits of the WSN system, the problem that limits the applicability of such system is the limited power and resource. WSN devices are battery powered devices in most cases. So they do drain out of power. The only way to get them working again is to replace the battery or somehow make provision for them to get recharged, i.e. using solar power. The different component in a sensor network node that consume power are,

2.3.1 Sampling

Sampling involves the steps of activating, sampling the sensor and deactivating it. This is power consuming process. Also each read takes away a little of a sensors life. So this is an expensive operation.

2.3.2 Processing

If the role of a sensor node has some tasks assigned that it performs on the data being sampled that consumes power. Both CPU and other hardware used for the processing.

2.3.3 Transmission

The most expensive component in the sensor node power hogs. Transmitting a data packet to the base station or to the fellow nodes for forwarding is a very expensive operation. The radio alone consumes an order of magnitude higher power than any other component in the sensor node system.

Given this background we will try to come up with a solution that attempts to solve the issue of sampling and then transmission. The rest of the chapters are as follows. Chapter 3 briefs some related works, 4 discusses the Adaptive Sampling technique followed by discussion of Smart Transmission in chapter 5. Chapter 6 and 7 presents Evaluation of the algorithm and future directions and we conclude with Chapter 8.

Chapter 3 Related Works

The use of Wireless Sensor Network for environmental monitoring application has been of interest for quite a while. Since there is a severe limitation of the sensor node architectures on the power consumption side, there has been several attempts using various techniques to minimize power consumption of such a network. [1][2].

Most of the techniques that are available nowadays tackle the power consumption problem by decreasing activity, employing lower duty cycle, periodic sleep etc. In [3] the authors describe a sensor network deployment in the arctic region in Norway. The system was used to measure the tilt, temperature, relative position etc. The network is similar in nature to that of SensorScope which this was is targeted for. Though they do not have explicit power management on their system, their observation does reveal the characteristic of such a network.

In [4][5][6] researchers have proposed Adaptive sampling techniques to eliminate the huge redundant sensing that is done to ensure coverage of interesting events. The key idea is to exploit known models of event occurrence to control the schedule of operation of the sensor nodes. In [5] the authors take the approach of hybrid automata in designing the control of the sensor nodes. The ability of hybrid automata to handle continuous monitored variables makes it more suitable for environmental monitoring networks.

Authors of [8] present a framework of weak detection followed by strong sampling to identify events and monitor them. In [7][9] authors presented collaboration techniques for power management etc.

Chapter 4 Adaptive Sampling

The first technique that we adopt to improve the power consumption in the system is adaptive sampling. Sampling is one of the key components in the total power consumption of the system. Main idea of adaptive sampling is to guess the behavior of the monitored variable and then adjust sampling frequency accordingly. So that events are detected when they are frequent as well as saving energy by skipping samples when events are not occurring.

4.1 Motivation

The main motivating factor behind doing adaptive sampling is the cost associated with sampling the sensors. Most of the sensors require a setup process followed by sampling and then a release process. Each of them consumes power. Another important side to it is the life of the sensor; most of the sensors are designed to deliver a finite number of readings. This is attributed to both electrical and device-wear along usage. In one word, sampling is a costly affair.

Secondly, from the understanding of the environmental variables, rapid changes in the values are in frequent. For example, in temperature sudden change of several degrees Celsius is very unlikely. And from the measurements that are available, it shows that the difference in readings is within the error margin of the instrument. So it makes sense to sample less often in the first place.

Finally, even though there is a certain rate of change in the variable being measured, it is only interesting to see the anomalies in the behavior. So it will make more sense if there is a system which can capture the anomalies without recording the regularities. Hence adaptive sampling rings the bell.

4.2 Existing Approaches

As discussed in the related works section, there have been a few adaptive sampling approaches towards sensor networks. The one we found suitable and applicable to a situation like environmental monitoring, is by Passos et al. [5]. They have used hybrid automata based controller to adapt to the changing environment condition. We will follow a similar approach in our system.

4.3 Boundary Cases of Sampling

Now the idea of adaptive sampling is clear, let's look at what we have at our disposal which can be readily thought of. Here are the two interesting cases of sampling strategies other than high frequency uniform sampling. Both of them provide power savings.

4.3.1 Uniform Minimal Sampling

The first case is the one with the minimum uniform sampling required by the field of application of the system. For example, measuring the ambient temperature of a place once a day does not provide much idea of the local climate. An example rate could be, say once an hour. The advantage of such a scheme is simplicity. This requires no complex logic and very easy to implement in a system. The problem is, the moment we fix the sampling rate at a lower level, the system starts loosing events. So the measurements are coarse and may not depict the subtle details of the behavior of the system.

4.3.2 Omniscient Sampling

The other end of the spectrum is sampling with full knowledge of the system. Which means the monitored variable is sampled exactly when an interesting change happens. This does not make much sense in a real scenario either because, there is not much need for sampling once it's known that change has happened.

4.4 Our Approach

Clearly from the analysis of the boundary cases one can see that to achieve useful results, one has to consider something in between the two. Here we present a very simple scheme for sampling. The default sampling interval is set to be high. The tendency of the measured variable is computed from the

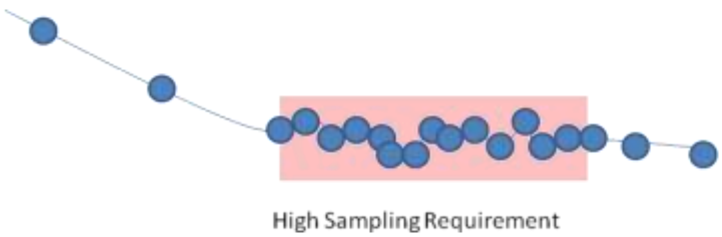

Figure 1: Sampling Rate Adjustment

previous values and is compared with every new sample. It increases the sample rate if deviation is observed and decreases if regularity is observed.

4.4.1 Hybrid Automata Based Control

Due to its capability of handling continuous control variables, a hybrid automaton is suitable approach for this. **Error! Reference source not found.** shows the parameters of the hybrid automaton used in our controller.

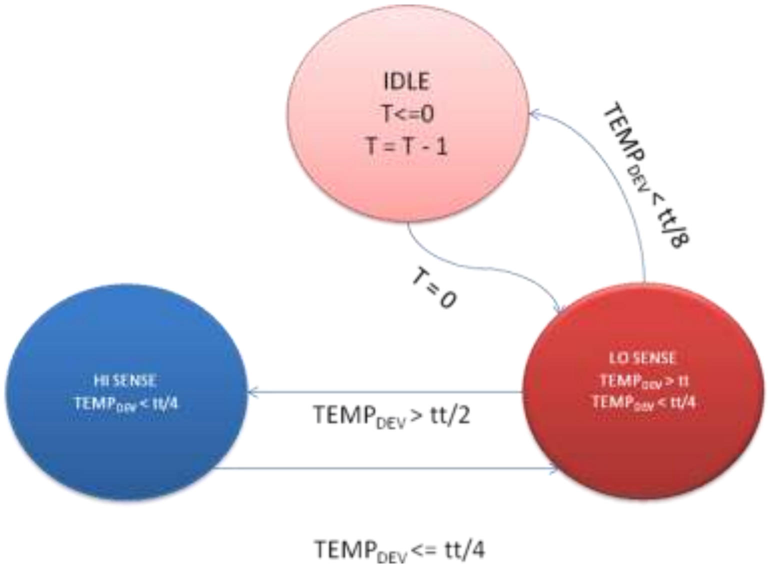

Figure 2 : Hybrid Automaton Used in Our Controller

Component	Description
IDLE, LOSENSE, HISENSE	Control States
T	Timeout
tt	Temperature Threshold
$TEMP_{dev}$	Temperature Deviation Computed as $T_{sensed} - T_{predict}$
Tsensed	Temperature from Sensor
Tpredict	Temperature predicted from model

Table 1 : Automata Components

4.4.2 Simple Temperature Model

In our system we have assumed a simple temperature model to predict the next sample value. It's a locally linear model with minimum two points.

$$Temp_{t+1} = \alpha Temp_t + \beta$$

The simplest case when $\alpha = 1$ and $\beta = Temp_t - Temp_{t-1}$

A more complex model:

$$Temp_t = A + B*t$$

A, B are linear regression coefficients

The second one was used in the later part of experiments.

Chapter 5 Smart Transmission

In this section we will explain how individual intelligence and collaboration among sensor nodes can enhance the energy efficiency of the system by making smart transmission decision. The smart transmission is done at two levels; Individual intelligence and Collaborative intelligence. We will discuss them in detail here.

5.1 Individual Intelligence

By individual intelligence we refer to the intelligent algorithm that every node employs based on its own information only. This does not consider the neighborhood information or anything else in making the sampling decision. The individual intelligent transmission algorithm is illustrated in Figure 3.

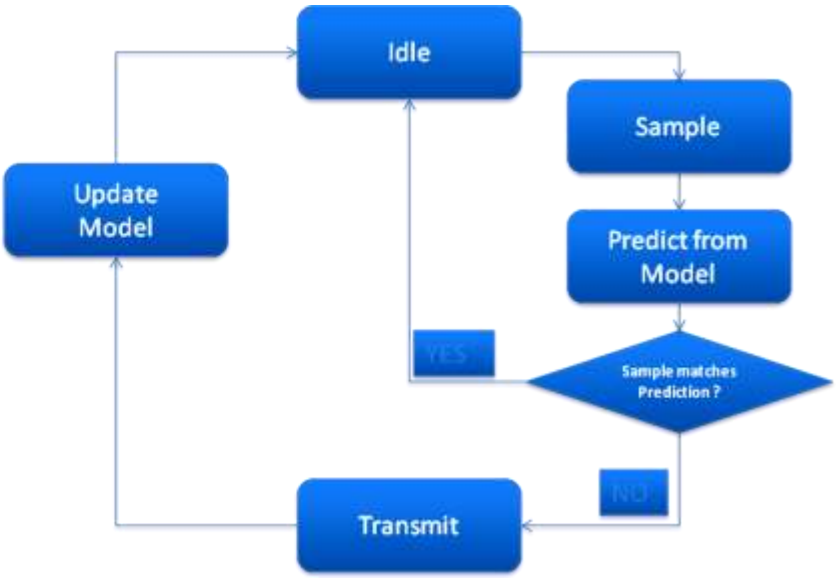

Figure 3 : Individual Intelligent Transmission Algorithm

The working principle of the algorithm is fairly simple. The node and the base station maintain the same prediction model for the measured variable. When a new sample is obtained it is compared to the prediction from the model.

If the sample is within an error boundary from the prediction, it is not transmitted. Otherwise the model is updated with the new value and it is transmitted. Similarly on the other side, i.e. the base station, if no value is received the prediction value is used. Otherwise the base station also updates the model upon receipt of a new sample.

5.2 Group Intelligence in Transmission

The second and more promising intelligence is using the neighborhood information. In this scheme the transmission decision is made based on the utility of the sample. We will define Utility later in this section. Before that, we'll discuss the affecting factors.

5.2.1 Utility of a Sample

The utility of a sample denotes its worthiness of transmission to the base station. Utility is a function of activity going on in the neighborhood, the randomness of the variable being measured, the cost of transmission and criticality of the data being measured.

Neighborhood of a Node

We define the perceived neighborhood of a node as follows,

Y is said to be the perceived neighborhood of x if,

$$\forall y \in Y, x \text{ can listen to } y\text{'s messages}$$

Spatial Correlation of Sample

In case of environmental monitoring application, the data that is collected is often highly correlated in space. As an effect of this, neighboring nodes are likely to sense similar data. This will be clear from Figure 4.

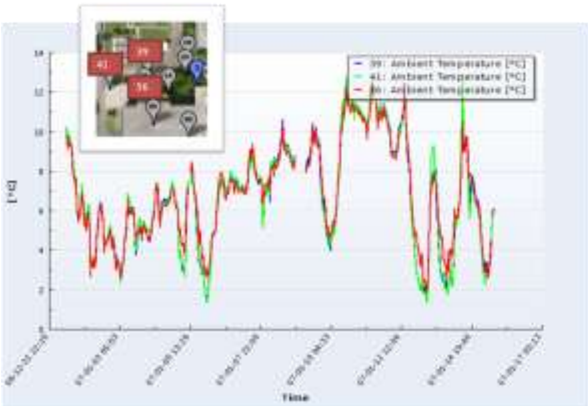

Figure 4 : Spatial correlation in Environmental Data

From this observation intuitive inference tells that if there are lot of activity going in the neighborhood, there is a fairly high probability of multiple nodes sampling similar values.

Criticality of Data

Not all measurements are equally critical. Some variables will have higher priority than others. So the utility should be able to capture this.

Temporal property of variable

If a measured variable changes often it should be measured more often so this. To capture this, the deviation from the model is used as the metric.

Considering the components discussed before we come up with a Utility function as follows,

$$U_i = \alpha D_i + \beta A_t + \gamma C_t$$

Where,

$$D_i = \frac{|S_i - \widehat{S_i}|}{R_{max}} \qquad S_i = i^{th}\ Sample\ taken\ at\ time\ t$$

$$\widehat{S_i} = prediction\ for\ time\ t$$

$$A_t = 1 - \frac{N_t}{N_{max}} \qquad N_t = active\ nodes\ at\ time\ t$$

$$N_{max} = nodes\ in\ perceived\ neighborhood$$

$$C_t = \frac{E_t}{E_0} \qquad E_t = energy\ level\ at\ time\ t$$

$$E_0 = initial\ energy$$

$$\alpha + \beta + \gamma = 1 \qquad R_{max} = instrument\ range$$

α, β and γ are constant coefficients. Their value decides the sensitivity towards the different factors discussed above.

5.2.2 Neighborhood Activity Monitoring

The neighborhood activity is tracked using special wakeup and sleep messages which every node broadcasts using a very low power. Every node maintains a set of active neighbors which is synonymous to |perceived neighborhood|. This information is used to calculate the Utility of a sample.

5.2.3 Utility based transmission algorithm

Based on the derived utility function we come up with this intelligent transmission algorithm that tries to minimize transmission of data to the base station when its importance to the base station is low. Figure 5 and Figure 6 illustrate the working of the algorithm. It is based on a hierarchical two tier automaton.

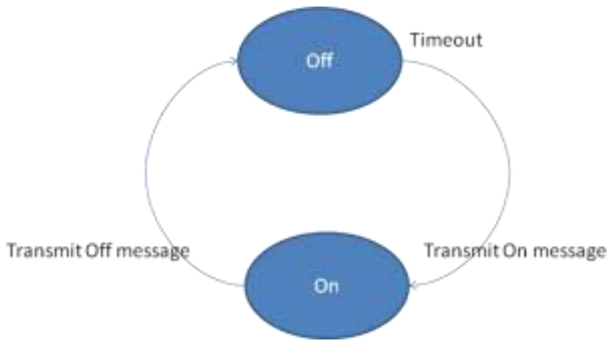

Figure 5 : Upper level Automaton

The two mother states of operation of the sensor node are 'On' and 'Off'. While in 'Off' state all the node does is to wait on a timer to wake up the node and it goes back to 'On' state. This decides the absolute maximum sleep time. On state is a little more complicated. While in on state it sends the notification messages while waking up or sleeping. It waits on a timer according to the currently enforced sampling rate. Samples, calculates the Utility according to the Utility function defined above. Compares with a threshold set by user and if it exceeds the threshold then it sends and updates the model or discards the sample otherwise. Figure 6 will illustrate the flow.

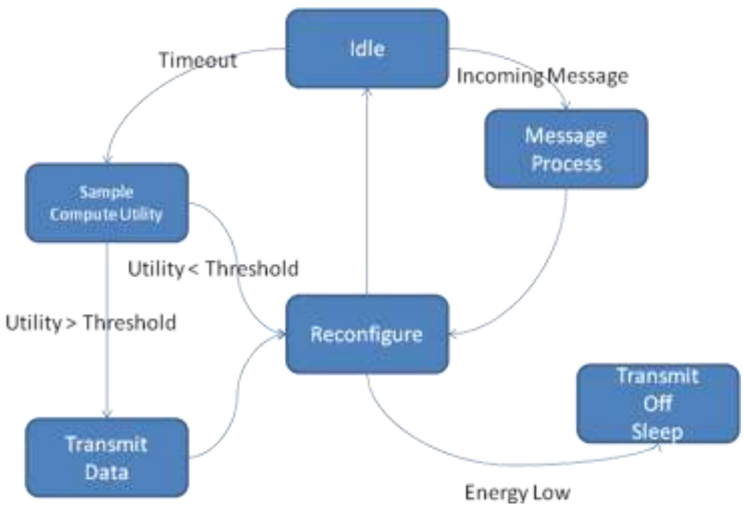

Figure 6 : On Automaton

Chapter 6 Evaluation

We have used simulation of the working algorithm of a sensor node to evaluate the discussed techniques. The results are being presented in two sections, namely results with adaptive sampling technique only. And results with adaptive sampling and collaborative transmission combined.

6.1 Results with Adaptive Sampling

This section will present the study with our adaptive sampling approach compared to no adaptation and uniform reduction in the sampling rate. We will briefly describe the simulation environment and the dataset being used. Followed by that will be the findings of the experiments.

6.1.1 Experimental Setup

Since this work is pure control algorithm based, we have chosen not to implement a real system simulation. Instead we assume that the number of samples taken by a given algorithm will give an idea of the power consumption involved. So we try to see if our algorithm reduces the samples taken over a certain period over time and in doing so does it perform better than simply reducing the sample rate to that level uniformly.

The experimental algorithm is run on a dataset obtained from a real sensing application called SensorScope that was being used for environmental monitoring in EPFL Campus. We assume the data obtained using the SensorScope system to be true and accurate and all our results are based on this assumption. It may be noted here that SensorScope system sensors are not accurate in fact, and deviation from real values can potentially alter the results. Yet, it is expected to see a similar behavior in real system as well.

6.1.2 Results

The findings of the first set of experiments were promising. We found that a significant savings of 98% can be achieved by using adaptive sampling on temperature data simply using the locally linear model described in Chapter 4.4.2 Here are the comparisons with plain uniform and Random reductions. Table 2 presents the comparison among the different sampling strategies simulated.

Samples w/o Adaptation	Strategy	Adaptive Samples	Reduction (%)	Mean Sqrt. Err. (% of range)
6854	Adaptive	125	**98.17 %**	**1.619 %**
	Uniform	125	**---**	**2.2%**
	Random	125	**---**	**2.07 (σ = 0.34)**

Table 2 : Comparison of normal and adaptive sampling

The closeness of the data obtained using adaptive sampling to the real data is illustrated in Figure 7.

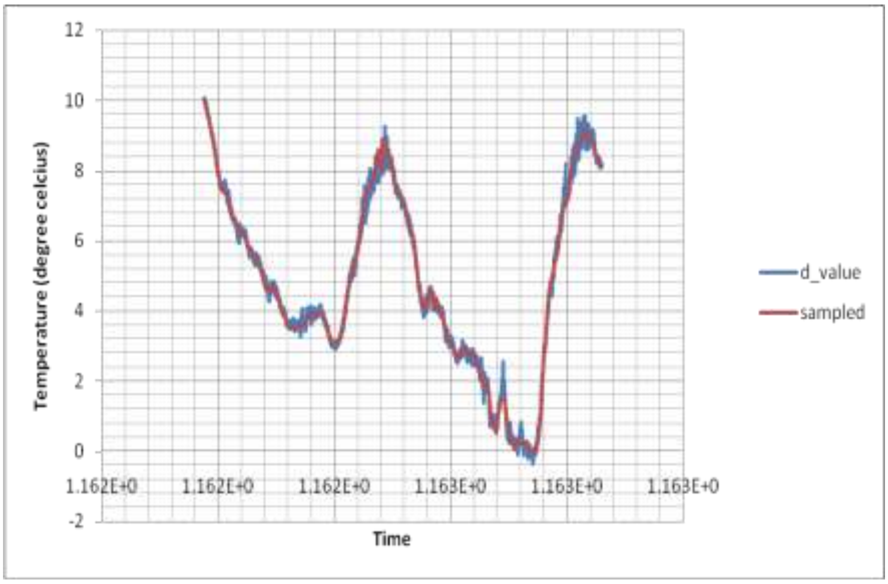

Figure 7 : Original and Adaptive sampled data

The system's ability to adapt the sampling rate to the variation of the environment can be seen in Figure 8.

Overall the algorithm is expected to improve power consumption by certain degree.

6.2 Results with Collaborative Transmission

In the second part of the experiments we simulated the behavior of the system where the sensor nodes collaborated among the neighbors to make decision regarding transmission.

6.2.1 Experimental Setup

The experiment was carried out on a set of two nodes communicating to the base station. Two though a small number the results of the experiment is scalable and is applicable to larger number of nodes. In this experiment we adjust the transmission threshold and see the transmitted data and calculate the error. From Figure 9 we see that increasing the threshold reduces the samples dramatically without increasing error level much.

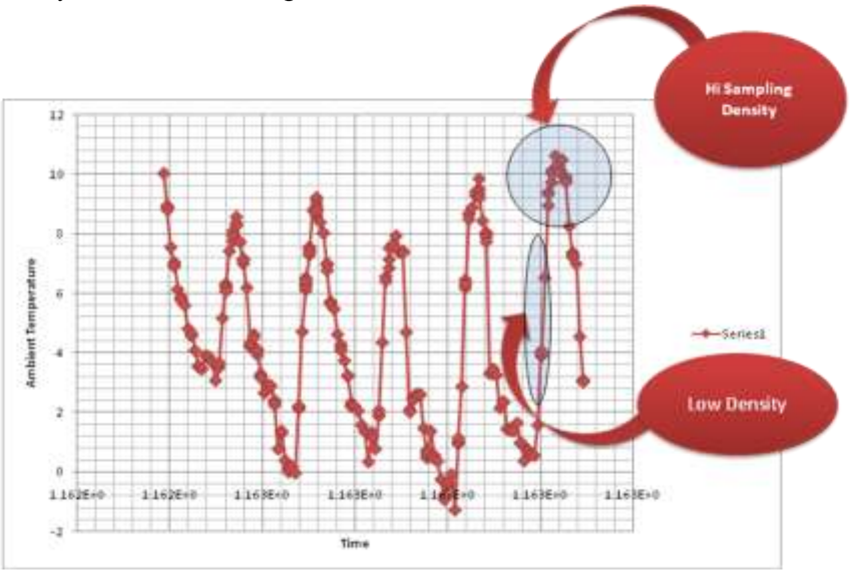

Figure 8 : Low and High sampling rates as required

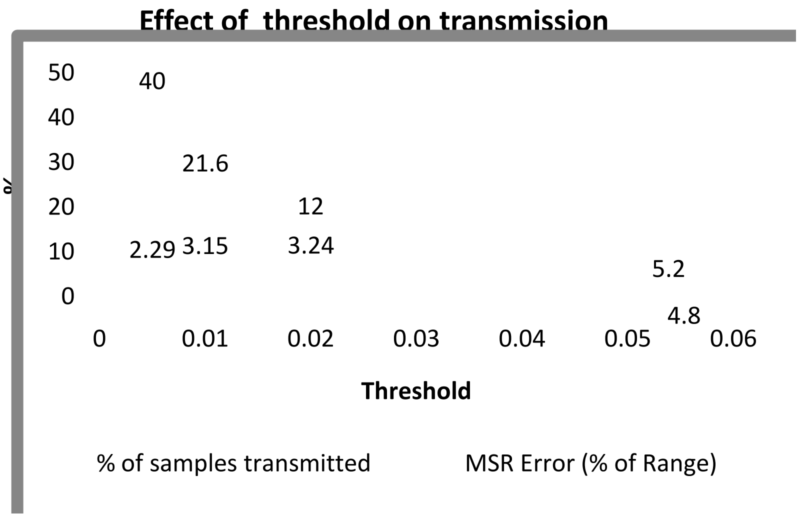

Figure 9 : Effect of Threshold on Transmission

Chapter 7 Future Directions

Full system implementation and deployment is the immediate next step for this work. In that direction, the first task would be to build a more realistic simulation environment that can estimate the energy consumption in the sensor nodes taking care of as many events as possible. Apart from those,

7.1 Improved Prediction Model

This requires better understanding of the monitored system. With more domain knowledge, one can possibly come up with a better model for the system. And having a better model will reduce the probability of missing an important event, ensuring even less sampling and transmission rates. This in turn adds to the power savings of the system. And in cases of systems where power is not an issue, the savings in resource usage can be utilized to increase the performance or individual node capabilities as well.

7.2 More Informative Communication

Instead of sharing just the activity information among the neighbors, there could be possibility of sharing more important and specific information about the status of a sensor node. Neighbors can use such information to estimate the state of the network and decide on its current role and act accordingly. The key idea is to identify bits and pieces of data that can carry significant information and identification of associated actions that can reconfigure the sensor node for an optimal operation.

7.3 Learning based approach

The present system described in here does not learn the behavior of the system that is being monitored. So it needs expert assistance to decide upon things like the required sampling rate, instrument accuracy etc. it will be nice to have a learning based system that can automatically configure its parameters as it operates in the environment. The key idea is to be able to throw a bunch of sensors and not having to look back.

Chapter 8 Conclusion

The studies carried out in this work have revealed the possibility of significant improvement in power consumption of an environmental sensor network without degrading the sensing performance of the system. It also reveals the fact that the quality of sensor and their accuracy often limits the sensing capability in both spatial and temporal dimension. As and when more capable sensors are invented, there will be requirement for fine tuning of the algorithms and techniques.

Another aspect is real system validation of the experiments that are performed in simulation. There is always a possibility of anomaly in the two of them. Hence a real system implementation and deployment would actually state the amount of savings and improvement achieved using this technique.

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