7-16-2007

A Physical Estimation based Continuous Monitoring Scheme for Wireless Sensor Networks

Wiwek Deshmukh

A PHYSICAL ESTIMATION BASED CONTINUOUS MONITORING SCHEME FOR WIRELESS SENSOR NETWORKS

by

WIWEK P. DESHMUKH

Under the Direction of Yingshu Li

ABSTRACT

Data estimation is emerging as a powerful strategy for energy conservation in sensor networks. In this thesis is reported a technique, called Data Estimation using Physical Method (DEPM), that efficiently conserves battery power in an environment that may take a variety of complex manifestations in real situations. The methodology can be ported easily with minor changes to address a multitude of tasks by altering the parameters of the algorithm and ported on any platform. The technique aims at conserving energy in the limited energy supply source that runs a sensor network by enabling a large number of sensors to go to sleep and having a minimal set of active sensors that may gather data and communicate the same to a base station. DEPM rests on solving a set of linear inhomogeneous algebraic equations which are set up using well-established physical laws. The present technique is powerful enough to yield data estimation at an arbitrary number of point-locations, and provides for easy experimental verification of the estimated data by using only a few extra sensors.

INDEX WORDS: WSN, DEPM

A PHYSICAL ESTIMATION BASED CONTINUOUS MONITORING SCHEME FOR WIRELESS SENSOR NETWORKS

by

WIWEK P. DESHMUKH

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree
of Master of Science
in the College of Arts and Sciences
Georgia State University

2007

A PHYSICAL ESTIMATION BASED CONTINUOUS MONITORING SCHEME FOR WIRELESS SENSOR NETWORKS

by

WIWEK P. DESHMUKH

Major Professor:	Dr. Yingshu Li
Committee:	Dr. Rajshekhar Sunderraman
	Dr. Anu Bourgeois

Electronic Version Approved:

Office of Graduate Studies
College of Arts and Sciences
Georgia State University
August, 2007

Acknowledgements

I am very grateful to my advisor Dr. Yingshu Li for introducing me to the subject of sensor networks and encouraging me throughout this work. She gave me invaluable guidance and support at every stage of this work.

I am very thankful to Dr. Rajshekhar Sunderraman and Dr. Anu Bourgeois for reviewing my thesis and for suggesting several useful improvements.

I wish to thank Chinh T. Vu, Shan Gao, Chunyu Ai and Yiwei Wu for their support and friendship. Working with them has been a very enjoyable learning experience.

I want to express my sincere and deep gratitude for the sustained guidance and encouragement I have received from Dr. Rajshekhar Sunderraman. I am very grateful to him.

- Wiwek P. Deshmukh

Table of Contents

List of Tables

List of Figures

I. Introduction

In a large number of situations it is necessary to take cognizance of physical observables using tools that are sophisticated extensions of our sensory perceptions. A ‘sensor’ is a device that is sensitive to a physical stimulus and produces a response that alerts us to the presence of a physical parameter. When the equipment used is calibrated to measure the quantity of the physical property being sensed, it provides for a quantitative measure of the physical stimulus.

A sensor is evidently an extremely useful device, since they extend the human sensory perception capability to ever increasing range. While the range of the human eye, for example, is restricted to a wavelength range of ~400nm to ~700nm (Fig.1.1), modern day electronic sensors can detect the presence of electromagnetic radiation well outside this range, and selectively identify various frequencies as well as the intensity of the radiation. Likewise, sensors detect temperatures that are extremely low, such as in the micro-Kelvin range, to extremely high - to several thousands of degrees.

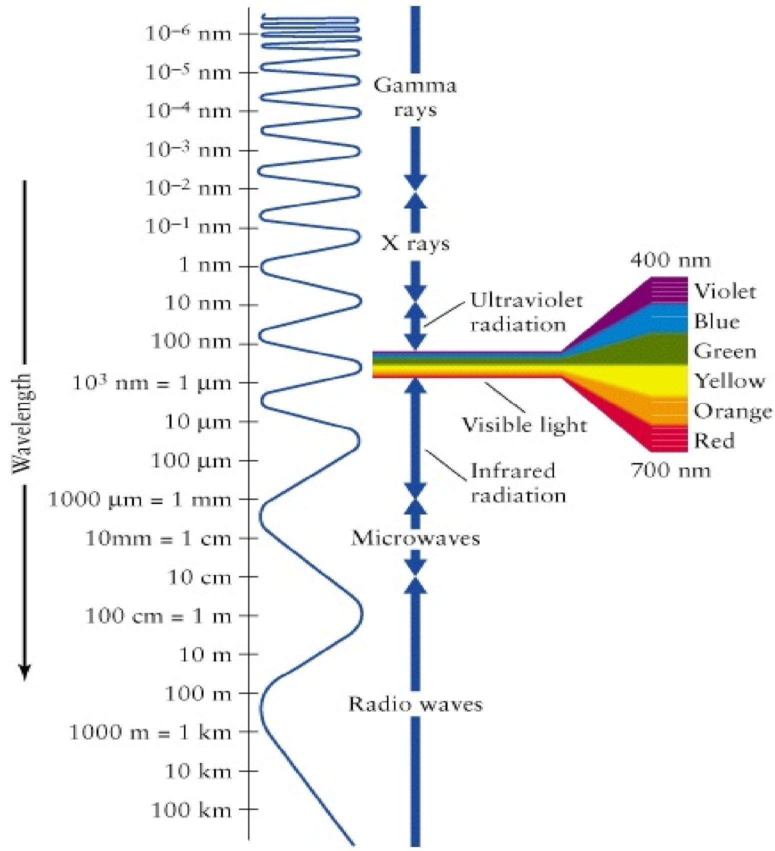

Figure 1.1: The electromagnetic spectrum [1]

In the early days of research and development in sensor devices, sensors merely detected and measured a physical parameter. A classic example is the thermometer. The Italian physician, Santorio (1561-1636) is credited for assigning first a numerical scale on a device that responded to changes in temperature [2].

Figure 1.2: Galileo's thermometer [3]:

Santorio's device was based on what was then referred to as a 'thermoscope' invented by Galileo Galilei who used the physical property that liquids of lesser density than water would 'float' in water at different heights, as shown in Fig.1.2, depending on the temperature. As the temperature changes, the height at which a liquid 'floats' would change and thus by reading the height one could gauge the temperature.

Clearly, these primitive devices were fully capable of sensing a physical property and indicate its quantitative measure. However, these devices did not have any microprocessor built into them, which were invented much later, so they were not equipped to process the information, Also, these devices could not communicate the information to remote observation stations, as they were not equipped with any transmission/communication devices which were also invented much later. The early sensors therefore needed to be in the very proximity of the observable physical property, often directly in contact with the physical property being measured. Modern sensors seek to obtain information about physical parameters that are caused by

sources that may be far and in a hostile environment, so they provide enormous extensions of man's sensory perceptions over wide ranges of space and time.

I.1 Perspectives in Remote Sensing

In order to get physical information about parameters that are influenced by sources or processes that are placed at far away distances, modern technology employs calibrated instruments that can respond to an external stimulus caused by the source or process in a measurable manner. The electronic technique based on the deployment of instruments/apparatus to acquire useful information about sources or processes that are spatially and/or temporally distributed in extended space and/or time in a manner that can be processed for fruitful applications is called 'Remote Sensing'.

The instrument placed remote from the source and/or process is the 'sensor', and it must have the capability to register (i.e. to 'sense') both a qualitative and a quantitative measure of the stimulus. The remote source and/or process is the object of surveillance and one may be interested in monitoring it either continuously and/or at regular or irregular periodicity. The recording device, namely the sensor, is not in physical contact with the central object of interest. The sensor devices depend on, for example, electromagnetic and/or acoustic phenomena stimulated through 'action at a distance' generated by the source target and/or process that is under surveillance. Sophisticated devices such as frequency-response amplifiers, scintillation counters,

magnetometers, radio-wave meters, seismographs etc. apart from cameras operating in various wavelength ranges of the electromagnetic spectrum are employed for this purpose. The term "Remote Sensing" was first used more than half a century ago, in the 1950s, by Ms. Evelyn Pruitt of the U.S. Office of Naval Research. The technique of 'Remote Sensing' is set in contrast to 'In situ' sensing in which the sensor device is placed in direct contact with the object of investigation.

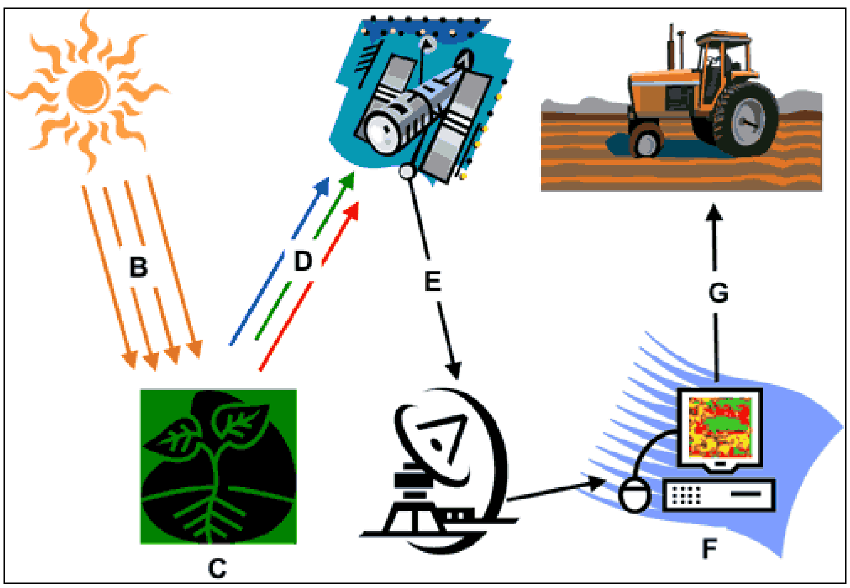

Figure 1.3: Block diagram of a complete 'Remote Sensing' process including the end user.

Figure 1.3 shows a remote sensing process [4] in which the sun (A) emits light, i.e. electromagnetic energy, (B), which is absorbed by plant (C). A portion of the electromagnetic energy is reflected, and/or re-emitted (D) which is detected by the remote sensor located on/in the remote satellite which transmits the data to the ground

station (E). The data is analyzed and processed by the computer system (F) and conveyed to the end user, the agriculturist (G).

The science of "Remote Sensing" is multidisciplinary in nature; it includes diverse fields such as applied physics, precision electronics, communication engineering, information processing, energy storage, mathematical modeling, computer science, simulation etc. Satellites equipped with remote sensors are now regularly employed to provide maps and classifications of geographical features, especially such as vegetation, soil properties, water reserves etc. Topological data are acquired and the information is processed using advanced technology in electronics and computer science, thus exploiting the developments in remote sensing methodologies for the fruitful applications.

I.2 Network Topology and Physical Constraints

In real applications, it is necessary to distribute a large number of sensors over an extended region of space and observations recorded by the sensors need to be collected, compiled, and processed for further application. A sensor network primarily functions using a distributed detection and estimation technique, and fusion of data from multiple sensors is fused for analysis [5]. As shown in Figure 1.4, a large number of independent sensors are deployed to record the physical information and the transducer in the sensor converts the observed stimulus into an electronic signal.

The electronic signals from the entire network are collated at the 'Fusion Center' where a 'Global Decision'. Essentially, a 'Parallel Fusion Topology' is implemented for data processing.

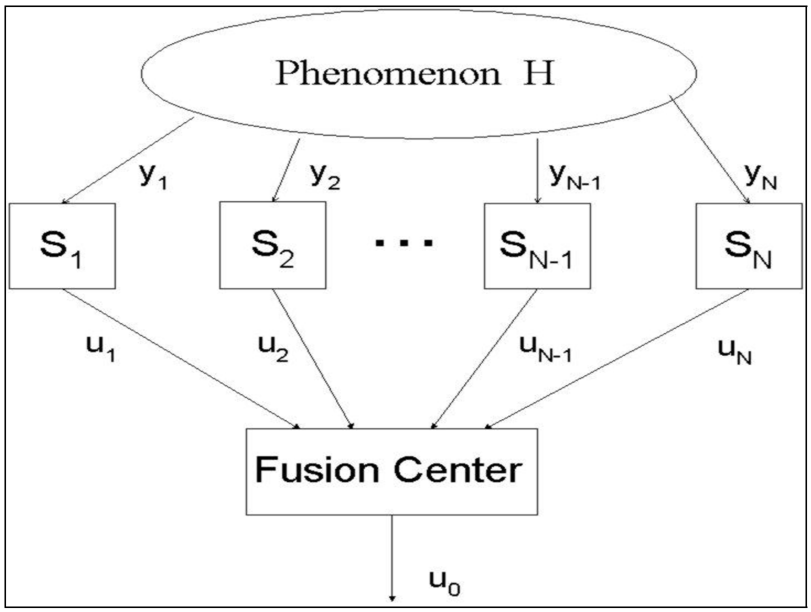

Figure 1.4: Parallel Fusion Topology [5]

Typically, a distributed sensor network that employs fusion of data consists of several sensors often spatially separated by vast distances. Sometimes, these sensors are designed to have characteristic features that are quite different from each other's and may in fact detect physical signals from different environments. Information from all of these is then gathered, processed and analyzed for further application [6].

Sensor Networks can be deployed in a variety of topological environments, including hostile ones. For example, detection of environmental hazards and monitoring remote terrain is a very common application. Applications range from tracking a tornado, forest fires, earth quakes, tsunamis, tracking military movements of a hostile nation, and detecting potential terrorist threats [7]. An example of locating a sensor in an extremely hostile environment is the industrial process of handling molten metal (Figure 1.5).

Figure 1.5: Pouring of Molten Metal [8]

If the level of the molten metal is automatically controlled using remote sensors capable of functioning in hostile super-hot environment, one can have an extremely cost efficient quality control that would eliminate the need of having a human worker being exposed to such a risky process where an error of any kind can cause serious injury to the staff member. The topological environment of the process is not merely

extraordinarily hot; the risk factor includes exposure to molten material's splatter [8], as seen in Figure 5. 'Vision Sensors' have become an integral part of manufacturing, with data registered by remote sensors automatically fed into the process technology in order to optimize the process functioning.

Figure 1.6: Sensor Housing for Molten Metal Environment [8]

Laser 3D sensors [8] encapsulate the sensors in a remote case away from the molten surface. The sensor case, shown in Fig.1.6, protects the sensor from the hostile environment. Sensors that are specifically designed for molten metal measurement are designed to secure optical filtering as well as electronic filtering to obtain a clear image of the laser spot on the molten metal surface. Network topology has to take into account several physical constraints, often very hostile, to extract maximum benefit from remote sensing technology.

I.3 Sensors that measure the intensity of EMR

A common physical parameter that can provide valuable information about a source is the intensity of EMR, i.e. Electro-Magnetic Radiation. The intensity of light follows a simple and strict mathematical law which relates the intensity at a given point to the distance from the source. Figure 1.7 [9] shows a very simple manifestation of the dependence of intensity of light (EMR=Electro-Magnetic Radiation) on distance from the source.

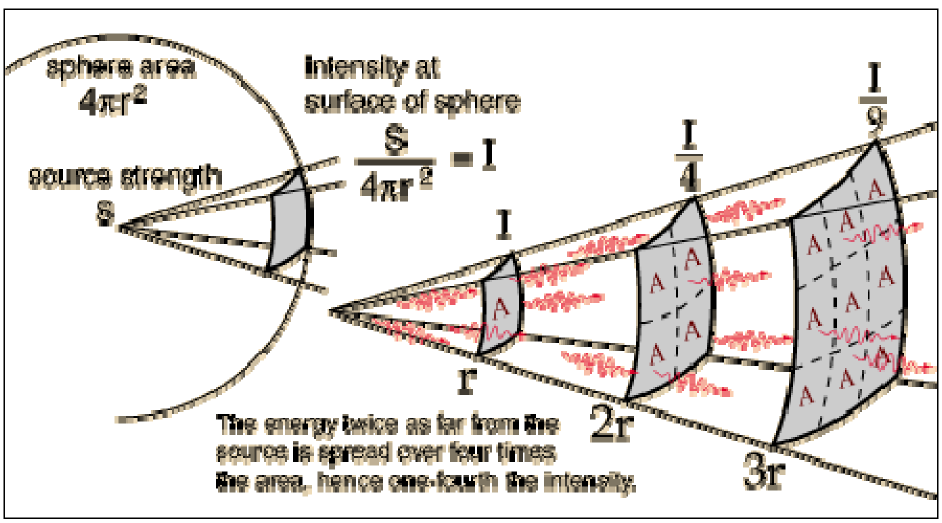

Figure 1.7: The inverse square law of light (EMR) [9]

In Figure 1.7, is shown a point source of light that radiates isotropic radiation (i.e., same amount in every direction). Radiation from such a point source intersects a spherical surface at a distance r, the surface area of which is $4\pi r^2$. If the strength of the point-light-source is S, then the intensity of light crossing unit area in a cone with

vertex at the light-source is S/$4\pi r^2$ and would diminish according to the 'inverse square distance' from the source, which is why this law of light intensity is known as the 'inverse square law'. Thus if a light sensor is kept at a distance d from a light source and is calibrated to measure the light intensity at that location, then the sensor reading can provide a measure of the strength of light source at a remote distance. This law depends only on the isotropy of the radiation emission and is thus geometrically exact.

The location in space at which the light sensor is kept is usually called as the 'field point' and the location at which the source is kept is called as the 'source point'. When more than one source is present, the light intensity at the field point follows the *principle of superposition*. According to this principle, the light intensity registered by a sensor is simply the arithmetic sum of the light intensity it receives from all sources reaching at the field point.

In the present thesis, a technique has been developed to achieve *energy conservation in Wireless Sensor Network using the Inverse Square Law of Electro-Magnetic Radiation.* This work is described in Chapter V.

II. Characteristic Features and Classification of Sensor Networks

An essential requirement of WSN (Wireless Sensor Networks) is the requirement for **energy conservation**. As discussed in Ch.I, a WSN is often required to function in hostile environments.

An efficient WSN would have following features:

- Hi-fidelity response to the stimulus under observation/surveillance.
- Reliable transducer mechanism that would convert the stimulus into a measure that can be used for further analysis.
- Communicate the measure of the stimulus to a base station where the information is processed.

In addition, a WSN would function very efficiently if the sensor is equipped with a mechanism to at least partially process the information that is registered. This is not an essential feature, but a very desirable one, since this feature can be exploited to program the sensor to communicate with other sensors. In WSN, each sensor is referred to as a NODE and sensor nodes are often programmed to undertake the following additional tasks:

- Decision making ability to communicate with other sensor nodes.
- Collate the data registered at a set of sensor nodes in the neighborhood of the sensor.
- Decision making ability to ‘communicate’ or ‘not communicate’ the data to a remote base station where the information is processed by the end user.

The above features enable a WSN to function as an energy efficient system since any amount of Information Processing and/or Information Communication requires energy consumption. The operation of the WSN thus consumes energy that must be stored in the sensor device to enable its functions.

A natural prerequisite of WSN is thus the development of sensors that (a) consume minimal energy for registering a quantitative measure of the stimulus from the source/process under observation/surveillance and (b) consume minimal energy to process and/or communicate the data registered.

II.1 Essential Characteristic Features of Wireless Sensor Networks

Sensor networks are now employed extensively to monitor events in distant regions and are equipped to operate often in extreme inhospitable environments. Technology has advanced by leaps and bounds and very sophisticated sensors are available to serve a number of applications. Sensor devices that are mounted on a tiny platform,

often the size of just a small coin, are now available. On these tiny devices are fabricated small instrumental gadgets which not only (i) produce a sensitive measurable response to a physical stimulus, but also (ii) process that information using a pre-programmed code installed on a microprocessor, (iii) select information for transmission to another sensor node and/or to a remote base station and (iv) communicate the processed information using radio-communication techniques.

In WSN, programmed sensors record physical data, process the information, communicate amongst each other and *identify using a pre-programmed algorithm one of the sensor nodes* in the network to communicate *select information* to a remote base station. The WSN connect various nodes using wireless communication devices a set of sensor devices that are distributed in a finite, but extended, region in which we are interested in knowing the quality and quantity of a certain physical property.

A vital feature in these networks is the role played by the particular sensor that communicates with the base station on behalf of the full network of sensors, or at least a set of nodes in its environment, thereby supplying information about the data available with all the sensors to a remote base station. This has the advantage that the base station gets information about the value of the physical parameter at all the sensor nodes in the network, *without* each node having to consume energy to transmit information. This is a crucial feature, since transmission of information is an energy

consuming process and it is essential in any technological environment that energy consumption is minimized.

Computers are now getting to be ubiquitous and smart devices that incorporate in their body, *that is only getting ever so tinier*, functionalities that have the capability to ‘sense’ and perform measurements, process observations, analyze the registered data and communicate select information to remote base stations using minimal power consumption. Accordingly, computer technology has increasingly embedded in itself developments in sensor technology – and vice versa! The composite devices can be used to manage security – whether residential or in a battle field, agricultural cultivation, health supervision, and what not.

A sensor node is therefore characterized by the following properties:

- Capability to gauge a physical property, process the acquired information and communicate the same to a remote base station.
- Tiny size and small weight: Continued miniaturization is enabled by ***Moore’s law*** which states that *the number of transistors on a tiny chip doubles in a very short while; the period estimated for this to happen has varied a little bit between 18 and 24 months* since the prediction was made first by Gordon Moore in 1965. The main contention of Moore’s law seems to have been upheld for four decades now [10].

- Minimal power consumption: This has been, and remains, the most important goal of modern sensor network technology.

II.2 Network Models

Classification of various sensor network models is usually referred to as the TAXONOMY of network models [11, 12]. Sensor networks serve in a variety of situations in remote areas. Sensors are placed in hostile environments to seek vital information transmitted to base stations. Varied techniques are employed to strategize economization of energy consumption employing a number of different models. Cataloguing of sensor models is therefore important, since there is no unique model on the basis of which sensor networks can be identified.

Sensor networks have to run on stored energy, so an important goal is to enhance the lifetime and operability of the sensors. The performance protocols of sensor networks are greatly influenced by two aspects: (a) mechanism employed by the networks to deliver the data to base stations and (b) mobility of the sensor nodes; i.e. whether the sensor nodes are static and fixed at their specified original positions or the nodes are mobile so that they transmit data from different physical locations, or perhaps transmit data at predetermined frequency.

Sensor network models are often classified in terms of *data delivery model*, and the *network dynamics* depending on whether the energy saving strategy is based on (a) or (b), above.

The following classification is suggested in references [11, 12]:

DATA DELIVERY MODELS

Sensor networks can be classified in terms of the data delivery required by the application (observer) interest as:

(i) Continuous Data Delivery Model:

In this model, the sensor networks perform observations and transmit the acquired information as data streams continuously to the base station. This obviously requires continuous usage of power consumption required in data stream communication, but in many cases this is essential even if it is not the most cost-effective mechanism.

(ii) Event-Driven Data Delivery Model:

In this model, information acquired by the sensor networks is transmitted to base stations only if a pre-identified event occurs and is detected/sensed by the network. As long as the event does not occur, no information is transmitted and this reduces the power consumption in the network operation significantly.

In Figure 2.1 is shown an example of a protocol for an efficient event-driven data-delivery model that functions in an energy-constrained environment and the sensor nodes are either static or mobile [13].

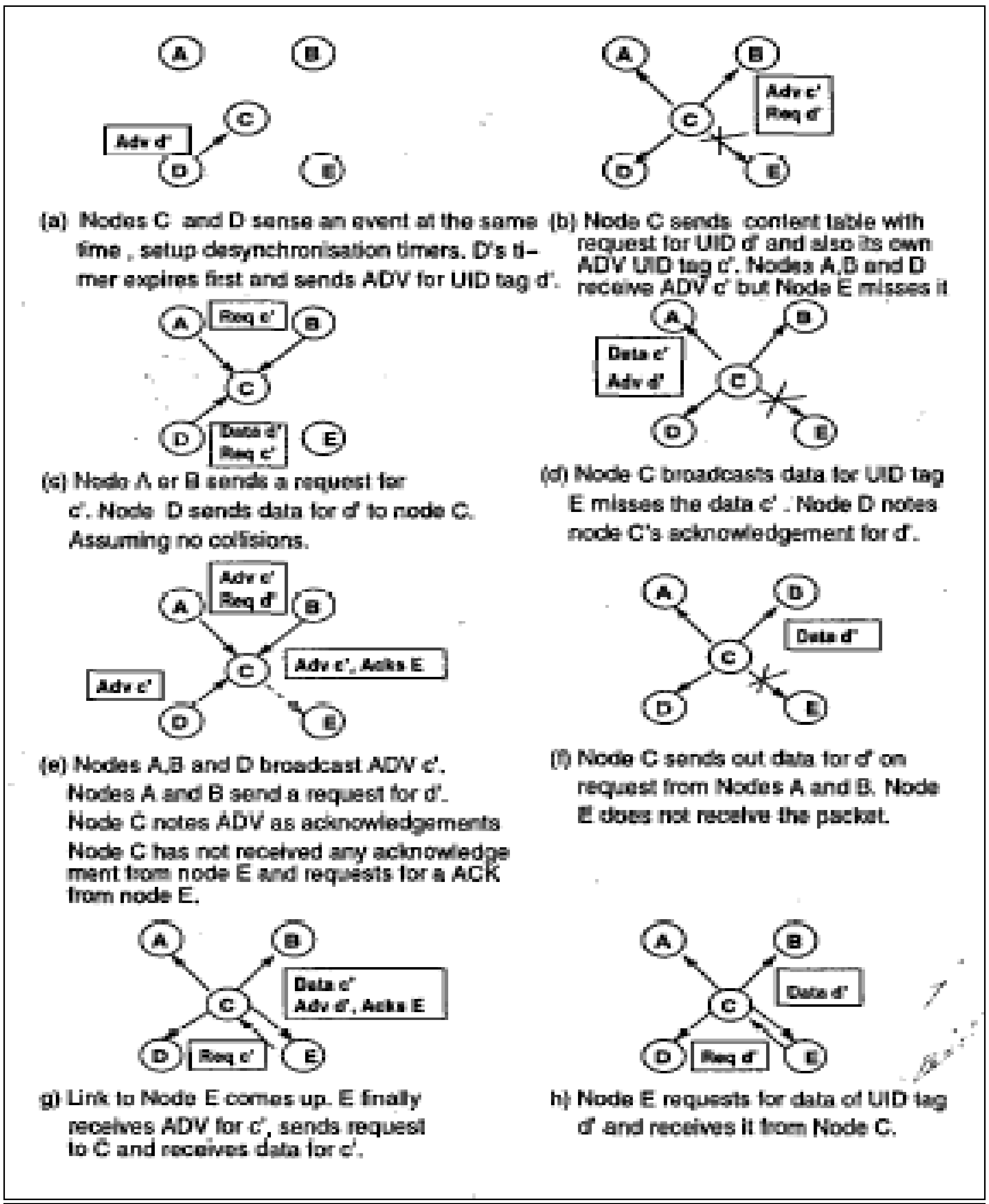

Figure 2.1: Data delivery in EVENT DRIVEN Wireless Sensor Network [13]

(iii) Observer-initiated Data Delivery Model:

In this model, the observer manning the network may trigger data transmission as and when she/he desires.

No data transmission takes place unless it is activated by the observer. This is useful and often sufficient; it necessitates energy consumption in data transmission only so activated by an observer.

(iv) Hybrid Model:

For practical applications, an actual sensor network requires a combination of the above models. Such networks are said to belong to the *Hybrid model*.

The DEPM technique developed in the present thesis is designed for the Continuous Data Delivery Model so that uninterrupted monitoring of source properties under investigation is possible.

NETWORK DYNAMICS MODELS

Having installed sensor networks in remote environments, further classification of network models is based on how the observer at the base station finally receives data streams transmitted by the networks. One needs to consider alternative methods of setting up pathways for the data streams to be transmitted from the sensor nodes to

reach the observer at the base station for her/his analysis. The choice of these alternative pathway modes depends on network dynamics, classified as: *static sensor networks* and *mobile sensor networks*.

Chapter III: Related Work

It would be clear from the discussions in Ch. I & II that an integral component of WSN technology is the energy saving strategy since sensor nodes are tiny devices sustained by stored energy which enables them to function.

Fuel economy can be achieved by requiring the sensor nodes to operate no more than what is minimally required for observation/surveillance, by requiring them to communicate, i.e. transmit information only as and when needed. In the present thesis, a technique is developed based on the exploitation of laws of physics that can be used to prepare a mathematical algorithm that enables a systematic control on the energy consumption of the sensor nodes permitting them to 'sleep' without compromising in the required information. The algorithm developed in the present work has been experimentally tested and will be described in Ch. IV and Ch. V.

In the present Chapter, a few related techniques that are aimed at energy conservation to enable a wireless sensor network function better, and longer, are reviewed rather briefly.

As mentioned in Ch.2, the energy saving strategies are primarily based on 'energy-conserving' data delivery models, and/or setting energy-efficient data stream management by employing innovative communication pathways for the purpose of

communication of the data streams from the sensor network to the base station. Various alternative modes of setting up network dynamics algorithms are set up for this purpose.

III.1 Data Management for Energy Conservation

A technique known as '*in network aggregation*' can be employed [14] to achieve reduction of data to be transmitted by a WSN to a base station, thereby reduction in energy requirement for communication. Query processing techniques are employed for data management, and hierarchical system models having two layers, a 'sensor network layer' and a 'proxy network layer' are used in conjunction with centralized and semi-distributed system models.

For efficient data gathering in wireless sensor networks, instead of making the entire cluster heads transmit to the base station, one can employ a new protocol [15] called PEGASIS (Power Efficient Gathering in Sensor Information Systems) which is based on the idea of building a chain in the sensor network with each node fusing incoming data with its own and passing it on to the next node on the chain. This way, the sensor data travels from the '*chain end*' to the '*chain leader*' which finally transmits to the base station. In PEGASIS, only one node transmits to the base station and in every round, a different node becomes the leader of the chain. This helps in a uniform consumption of sensor node energy. Details on how the chains for different cases

such as (i) for CDMA capable sensor nodes and (ii) Non-CDMA sensor nodes are also developed. This technique uses the d^2 radio communication power dissipation model and uses energy x delay as the metric to minimize.

Advantages of PEGASIS:

(i) It saves energy in several stages. In the local gathering, the distances that most of the nodes transmit are much less compared to transmitting to a cluster head in LEACH.

(ii) The amount of data that the leader of the chain has to receive is at most 2 instead of as many nodes in a cluster.

(iii) Only one node transmits to the base station.

‘*Approximate Data Collection in Sensor Networks using Probabilistic Methods*’ [16] such as *in-network aggregation* acting as data reducing operators have also been proposed to reduce the energy requirement of the sensor networks. However, sometimes applications/researchers need complete data-sets from the sensor network. In such cases, usually, approximate data is sufficient. One can thus design a data gathering technique using replicated dynamic probabilistic models, such as KEN [16].

In the technique ‘KEN’, a data estimation model runs in the sensor network (referred as ‘source’) and a copy of the same model runs at the base station (referred as ‘sink’). The base station keeps estimating the values of the physical parameter that is sensed by the sensor nodes which is required to communicate the data to the base station if and only if the sensed value differs from the estimated one by a factor that is larger

than a prefixed error margin. Since the sensor network runs the same copy of the estimation model as the one run at the base station, this conditional transmission does not cause any loss of critical information. The estimation model itself can be dynamically updated as new data comes in from the sensor network thus enhancing the power-saving capability of this method.

Another power-saving strategy is based on the often prevailing situation that sensors in a sub-region have strong spatial correlations with each other and hence a subset of sensors is sufficient to gather correlated data of the entire sensor network. To exploit this feature, one must look for '*Correlated Data in Sensor Networks*' [17]. This method is concerned with how to find a connected correlation-dominating set M, which is sufficient to predict the sensed values of all other nodes in the sensor network. In this method, a *correlation graph over the sensor network* is defined as a directed hypergraph G(V,E) where V = set of all nodes in the sensor network & E is a subset of (P(I) x I) where P(I) is the power set of I. The goal is then to find a minimum connected correlation graph. The least-squares (LS) method is then employed to minimize the error in calculation of a hyper-edge in computing the correlation graph; and a *Handshake Algorithm* is developed to select a connected-correlation-dominating set in the sensor network.

In a technique called '*CONCH: Constraint Chaining: On Energy-Efficient Continuous Monitoring in Sensor Networks*' [18], the authors propose a continuous

monitoring scheme suitable for continuous queries. The main idea used in this paper is to heavily use temporal & spatial suppression to achieve energy saving. Since in a sensor network, most of the values that are monitored are either temporally or spatially correlated, one may infer the value if it has not changed from the past value such that not every value is needed to be reported in every time-step. The authors first give a simple method called NEIGHBORHOOD which uses spatio-temporal suppression. They then point out the drawbacks of this method and propose a novel method called **CONCH (Constraint Chaining).**

The main idea in CONCH is to first build a minimal cost spanning forest of the sensor network. The cost is defined as the expected energy cost of monitoring calculated using past historical data. (It should be noted that the CONCH forest may be different from the routing tree of the network. The CONCH forest is only used for data collection. A different routing tree may be used for the purpose of reporting). In the next step, the spanning forest is taken as input and for each edge of the forest, a reporter and updater is assigned. The job of the reporter is to report the difference along the edge (if changed) to the base station (BS) and the job of updater is to update the reporter of the edge with its value (if changed). The optimal role assignment is modeled as a linear program.

To take care of failures, the authors propose to incorporate redundancy into CONCH by having multiple forests built and using the rule that an edge or node is monitored if

it belongs to any of the spanning forests. Value reconstruction can be done in one pass using a topological sort of the constraint network at the base station. This method can only be used when sensor values are spatially or temporally correlated. The method is not dynamic and uses periodic re-optimization at the base station to build new CONCH plans; the authors however suggest a 'local adjustments' which can be made to make it partially 'dynamic'.

'*TAG: a Tiny Aggregation Service for AD-Hoc Sensor Networks*' [19] is an aggregation service, called TAG, which provides a declarative interface for data collection and aggregation. The main idea of this paper is to propose in-network aggregation and compare it to the centralized approach where all sensor readings are sent to the base station and the aggregate is computed at the base station. The authors show that in-network aggregation can achieve an order of magnitude performance improvement over the centralized approach. The TAG algorithm itself is a tree-based approach where data is collected and aggregated as it travels from the leaves to the root of the network routing tree.

The authors give a detailed study of the different kinds of aggregates that can be computed in-network and broadly classify them as:

1. duplicate sensitive aggregates
2. exemplary vs. summary
3. monotonic vs. non-monotonic

4. amount of state required for each partial state record.

The TAG algorithm is heavily dependant on timing synchronizations and can perform adversely with clock skew. The authors assume that the network has a maximum depth d, and set the duration of each interval to DURATION(root)/d. However, delays caused due to failures are neglected. A major concern with TAG is that a single failure results in an entire sub-tree of values being lost.

III.2 Routing Techniques for Energy Conservation

Essentially, data gathered by the sensor network has to be delivered to the base station, but depending on how the data are transmitted from the sensor nodes to the base station, the amount of energy that is consumed can be quite different depending on what alternate pathways are selected to route data communication.

Typically, data is routed through some gateways and the network would cease to function if a gateway node runs out of its stored energy supply. At any given point of time, the 'residual energy', i.e. the 'remaining energy' of each gateway must be optimized and hence data must not be transmitted on a single route wherein the residual energy of a gateway gets quickly burnt up. In a technique called '*Optimization of Task Allocation in a Cluster–Based Sensor Network*' a method is developed [20] in order to optimize the 'remaining energy' of the gateway nodes

(cluster heads). It is assumed that cluster formation is done by the Command Node (Base Station) and that the command node acts as a task arbiter between the gateways. An objective function is developed in terms of the resources such as available processing capacity and available inter-gateway communication bandwidth etc. per cycle. Also, constraints such as *schedulability conditions*, bound on available communication bandwidth per gateway for interaction with sensors in the cluster and other gateways, are applied to the objective function. The task allocation to gateways is modeled as a ‘zero-one’ non-linear goal-programming problem. A method called ‘Simulated Annealing Optimization’ (Derivative Free Optimization) is used; experimental results show that by optimization of task allocation between the gateways produce a higher ‘minimum remaining energy’ as compared to the situation when such optimization is not used. This resulting routing prescription helps in maximizing the lifetime of the gateways.

Query Processing for Sensor Networks [21] is a methodology in which is built a *query layer for sensor networks* to handle simple queries of the form:

```
SELECT      {attributes, aggregates}
FROM        {Sensordata S}
WHERE       {predicate}
GROUP BY    {attributes}
HAVING      {predicate}
DURATION    time interval
```

EVERY time span e

Techniques are developed to integrate the two processes *computation* with *communication* in sensor networks and options of ‘Direct Delivery’, ‘Packet Merging’ and ‘Partial aggregation’ are addressed for efficient data transmission. Synchronization can be achieved between *parent-children* nodes in the DAG/Tree Structure used as the suitable communication structure with timers and notification packets being used for bi-directional synchronization. In this method, it is shown that the commonly used wireless routing protocol AODV can be modified suitably for *in-network aggregation*. It is found that in order to implement in-network aggregation, intermediate nodes must be able to intercept data packets whose final destination is the leader node or the gateway node. Query optimization is further optimized such that the query plan decides how much computation is pushed into the network depending on specific requirements.

In a technique called ‘*GHT: Geographic Hash Table for Data-Centric Storage*’ [21], various data dissemination methodologies have been discussed and compared with each other. The main data dissemination techniques are:

1. External Storage
2. Local Storage
3. Data Centric Storage (DCS)

DCS is preferable in cases where the sensor network is large and there are many events, not all of which are queried. The main idea in DCS is to store all detected

events of the same type having key K at the same node within the sensor network. The node at which this data is stored may not be the node which detected it. The advantage is that all queries related to a particular event can be directed to a particular node, hence conserving energy. A *Geographic Hash Table (GHT)* is proposed so that for every event key K, there is one *hashed* location & for every *hashed geographic location*, there is one *home node* which is closest to it. The data is stored at the home node. To take care of the dynamic nature of the sensor network with nodes failing, a Perimeter Refresh Protocol (PRP) is provided. Also, if too many events with same key are detected, the home node can become a single point of failure called 'HOT SPOT'. To avoid this, *Structured Replication* is used.

A factor of crucial concern in sensor data gathering and communication is the conservation of sensor energies, so that the lifetime of the sensor network is maximized. 'Data fusion' or 'Data Aggregation' has therefore emerged as a very powerful tool to minimize energy consumption involved in data transmission. The essential idea in this strategy aims at combining data from different sensors so that any redundant data that need not be transmitted is eliminated. One thus aims for '*Maximum Lifetime Data Gathering and Aggregation in Wireless Sensor Networks*' [23]. In this paper, the authors give an efficient way to perform data gathering with / without aggregation in sensor networks. First an admissible flow network is obtained using an integer program that runs in polynomial time, maximizing the lifetime T of a schedule. This problem is modeled as a maximum flow problem. The schedule is basically a set of T directed trees rooted at the base station. The schedule has a lifetime T which is to be maximized. Each tree gives us how data packets are gathered & transmitted to the base station. Next, using another algorithm which takes

the admissible flow network as input, a set of aggregation trees are obtained to constitute the schedule.

In another routing strategy, '*LPT for Data Aggregation in Wireless Sensor Networks*' [24], the authors propose to build aggregation trees for in-network aggregation which they call as Lifetime Preserving Tree (LPT). In LPT, nodes having higher residual energy are chosen as the aggregating parents. The LPT itself has the property of self-healing by which the aggregating tree can be re-constructed whenever a node dies or some broken link is detected. In their approach, the authors use 'remaining energy' as the key metric so as to prolong the time before a tree needs to be reconstructed, hence reducing the maintenance cost. The tree energy is defined as the energy of that non-leaf node having the minimum energy in the tree. The problem then reduces to finding a spanning tree having the highest tree energy. The authors give both centralized and distributed algorithms to re-construct the aggregation tree. The main idea in the algorithm is to try to see if we can afford to keep a node as a leaf-node by disconnecting it to all other nodes except its maximum energy neighbor. Only if the graph is still connected, the disconnection is possible. If not, the node cannot be a leaf node and must be parent to some other node. Also, the node being the least energy node (since nodes are considered in order of increasing remaining energy), it is the bottleneck node and tree energy is the energy of this bottleneck node. The simulation results indicated that the centralized and distributed algorithms give more or less similar results and are better when compared to Directed Diffusion and E-Span.

A technique that combines the advantages of data aggregation and efficient routing protocols to minimize energy consumption is '*Data Funneling: Routing with Aggregation and Compression for Wirelesss Sensor Networks*' [25]. In this paper, the authors propose a simple method of data aggregation. Here the main idea is to form clusters in the sensor network and perform in-network aggregation at the cluster

heads to achieve energy saving.

Directional flooding protocol is used to send out an ‘interest packet’ to a particular region (cluster). The first nodes belonging to the intended region to receive the ‘interest packet’ become the border nodes. A region may have many border nodes and only one of them is selected to be the region head which will aggregate all packets within its region to send back to the controller (base station). The border nodes modify the interest packet to accommodate cost of reaching the controller through itself and number of hops to the border node. All nodes within the region select that border node which has the minimum cost of reaching the controller.

Furthermore, in this technique, the authors propose a coding technique which can be used to compress the aggregated data to be sent back to the controller at the border node. They employ a coding by ordering method where some packets are suppressed and their values are encoded by the relative ordering of the remaining packets.

Nevertheless, a primary concern in this technique is the fact that the same border nodes are used in every round, and this would deplete the energy of the border node. Besides, failures of border nodes or sensor nodes are not taken into consideration. The authors suggest that the different border nodes may take turns acting as the cluster-head but no further details are provided. One must note, however, that the coding by ordering encoding process will work only if the value suppressed is within

the no. of possible orderings. To solve this problem, complicated numerical methods have to be employed at the border node. Unfortunately, it seems that the encoding-decoding process is not energy efficient and has to use large look-up tables.

Also developed is a technique in which data aggregation using 'Synopsis' and Multi-path Routing' is employed [26] to make the aggregation framework more robust compared to tree-based approaches, as in TAG [19]. The 'synopsis' designed are *Order and Duplicate-Insensitive (ODI)*. The double counting problem which is usually associated with multi-path routing is solved by decoupling the aggregation from the message routing. The authors implement this over an underlying topology called 'adaptive rings' where they build concentric rings around the querying node and each node in the ring generates a synopsis of the aggregation value combining its own value to synopsis that it receives from nodes which are 1 ring outer. This is as opposed to the aggregation method used in TAG where the nodes combine the aggregation value to its own value. The output of a 'synopsis' is the same no matter how many times it may receive the values through different paths and is also insensitive to the order in which they arrive.

A novel approach which combines the advantages of two popular aggregation topologies is the following: Most of the aggregation strategies developed so far, fall into two categories namely tree-based or multi-path based approaches. The tree-based aggregation is simple and gives accurate results but performs adversely with failure of

nodes and multi-path aggregation performs much better with node failures but aggregation result may have large approximation error. Also the message size may be too large. A technique called '*Tributaries and Deltas: Efficient and Robust Aggregation in Sensor Network Streams*' [27] aims at combining the relative advantages of these two schemes by allowing some portion of the network to run a tree-based aggregation and the remaining part to run a multi-path algorithm. The selection of which approach to use is done based on the current loss rate. If the loss rate is high, then the multi-path scheme is preferred as it is more robust to communication / network failures. The authors give the necessary and sufficient conditions for the correctness of their algorithm and then propose a tributary-delta algorithm for a particular aggregate: finding frequent items. They also propose a multi-path algorithm for finding frequent items. In this methodology, the base station has to frequently update the network topology according to the current loss rate.

In a '*Highly-Resilient, Energy-Efficient Multi-path Routing in Wireless Sensor Networks* ' technique [28], the authors suggest an alternate way of setting up multi-paths from a single source to a single sink for data aggregation. One may note, however, that in this work, for energy-efficiency reasons, paths are constructed on-demand rather than proactively. Furthermore, to make the method robust, a periodic low-rate flooding scheme notifies the sink and other nodes of available alternate paths. The periodicity of flooding determines the temporal accuracy of alternate path characteristics.

The major drawback of this scheme (as in Directed Diffusion), from energy-efficiency point of view, is the periodic flooding of low-rate events. This paper considers mechanisms that allow restoration of paths from source to sink without the periodic flooding. These mechanisms are based on some observations: while setting up the path between a source and sink, it may be possible to set up and maintain alternate paths in advance (with some extra energy) to minimize the possibility of having to invoke data flooding for alternate path discovery. The main contribution of the paper is to proactively maintain braided multi-paths which are different from the primary path but may not be completely disjoint. Therefore, there is a better chance that the alternate path is closer to the ideal alternate path hence reducing energy requirements for route maintenance. The alternate route maintenance overhead problem is however not solved, and still consumes much of the sensor's energy.

III.3 Power saving by way of filtering data

Chu et al., [29] have proposed a mechanism, using conditional data transmission to conserve battery power by seeking data collection only if the information sought is beyond bounds predicted using statistical models based on certain temporal and spatial correlations that can determine predictable stable states. Jain et al. [30] have built dynamic procedures that employ maximum altering of data using a technique called .stochastic recursive data altering, to conserve resources subject to meeting precision standards. They have employed Dual Kalman Filters (DKF) to achieve this.

Both models mentioned above employ statistical techniques which have emerged as one of the most powerful strategies to reduce data collection and acquisition by substituting real values of physical parameters by their statistical estimates using well tested statistical models. Such strategies provide significant relief from energy consumption.

Primarily, these methods are aimed at reducing energy consumption by substituting '**data acquisition**' by '**data estimation**'. Another method of data estimation is based on collection of data samples for a relatively long time and calculates the autocorrelation of the vector of samples [31]. In this method, bio-inspired field estimation for sensor networks has been used. Field estimation is an important application of wireless sensor networks. This type of application deploys sensor nodes in a specific region to remotely sense space and time dependent processes. Reference [31] aims at enabling sensor nodes to identify patterns in the behavior of the sensed processes and report only uncommon observables. In this scheme is exploited the temporal pattern of the sensed process to reduce the number of samples sent back by a sensor node to the sink and thereby reduce the energy consumption in data transmission. This scheme employs temporal parameters as opposed to spatial parameters that can also be used toward sampling reduction to conserve battery power. This environment-aware behavior is similar to the response of living beings to the surrounding events.

Lazos et al. [32] have developed a WSN technique for secure position estimation which they have called as ROPE: Robust Position Estimation In Wireless Sensor Networks. They have dealt with the problem of .secure location determination, and have addressed the problem of verifying the location claim of a node, known as Location Verification, in Wireless Sensor Networks (WSN). ROPE allows sensors to estimate their locations without any centralized computation. In addition, ROPE provides a location verification mechanism that verifies the location claims of the sensors before data collection. Bounds for frequency estimation of packet streams have been investigated [33] considering the problem of approximating the frequency of frequently occurring elements in a stream of length n using only a memory of size m << n. This models the process of gathering statistics on Internet packet streaming using a memory that is small relative to the number of classes of packets.

In essence, most common techniques to save battery in sensor networks employ strategies to minimize data acquisition and/or transmission by using a variety of approaches. In the DEPM technique developed in the present work, for the first time physical laws are employed for data estimation as a direct energy saving strategy. Other methods predominantly exploit temporal and/or spatial correlations and/or data filtration for data estimation, whereas DEPM employs well-established and rigorous laws of physics directly in the sensor network plan to achieve minimization of energy consumption.

Chapter IV: Data Estimation using Physical Method (DEPM) to Conserve Energy in WSN

In this Chapter is presented an energy saving mechanism in which data estimation is achieved using fundamental laws of physics. The essential idea is that if data can be reliably estimated, then it need not be communicated nor acquired by a sensor, thus effecting huge energy saving. Conserving energy is essential, considering the fact that networks technology needs to deploy sensors often in hostile and/or inaccessible environments where their power source cannot be easily replenished.

The techniques aimed at minimization of energy usage described in Ch.3 primarily employ one of the following two strategies, or *a combination thereof*:

(i) Data Aggregation

- *aimed at minimizing the data that must be transmitted thereby reducing the demand on power consumption.*

(ii) Energy-Efficient Routing Protocols

- *aimed at optimizing the pathways that must be employed for information transmission from a remote sensor to the base station for end use.*

Mathematical and Statistical Models are employed in data aggregation techniques. For the most part, ***data reduction*** is aimed for by employing ***data estimation*** by

exploiting spatial and/or temporal correlations and using predictive ability of mathematical/statistical algorithms.

Another mechanism of achieving data reduction is by way of employing laws of nature that determine the physical parameters that are being sensed.

In the next Section, a few techniques that employ ‘physical laws’ for data estimation are reviewed, and subsequently, in Section IV.2 is developed an algorithm that is based on the Inverse Square Law of the Electro-Magnetic Radiation that enables enormous amount of energy savings by using a fundamental and well-established law in Physics. It has the advantage that its accuracy is very high and it is thus a very reliable tool; its accuracy is not affected by statistical random errors/fluctuations.

Data acquisition and analysis is an essential ingredient of current technology and is enabled by wireless sensor networks that have the capability of collecting physical information on a mammoth scale. Automation provides relief from human involvement that is otherwise impractical in a vast number of real situations, but requires stored energy in sensor devices that must work in hostile environments and have long life. Due to the energy limitations faced by the sensor nodes, most techniques focus on aggregating data *in-network* so as to reduce the communication costs and improve energy efficiency. Although this is a good way of conserving energy, at times it may be necessary that all sensor readings be collected at the base

station. In such a scenario, *in-network aggregation* cannot be permitted as it reduces the data-set communicated to the base station. In such situations, data-estimation can prove to be very fruitful.

Sensors work in rounds in a network. In a given round, a minimal number of sensors are required to be active and communicate information to the base station. In order to save battery power on which the sensors work, the information communicated by the active sensors must include the values of physical parameters that even the sensors in sleep mode would have supposedly recorded. The active sensors must thus perform their own designated functions, and also substitute for the function that would be performed by the sensors in .sleep mode, within a tolerance limit.

An example of this kind is the determination of light intensity distribution in a region that needs to be known for certain applications, such as photosensitive horticulture under artificial illumination [34].

Commercial gadgets are now available [35] of this kind; for example, the HortiSpec (Figure 4.1) was developed to measure the light intensity and spectral distribution in the visible and NIR range inside greenhouses. Plant growth and the photo synthesis depend very much on light intensity and spectral distribution of the light intensity. The light intensity can be measured by these sensors and data estimation techniques

employed in such environments would help conserve battery power of the sensors and increase the life of the sensor network.

Commercial light sensors which use photodiodes that produce a voltage proportional to the light intensity are now available.

Figure 4.1: The HortiSpec can be connected wireless via Bluetooth to a distant computer. The computer can then be used to control the movement of screen filters in the greenhouse or to control special lamps. It was developed to measure the light intensity and spectral distribution in the visible and NIR range inside greenhouses.

Similarly, light intensity sensors are required to monitor maintenance of optimum lighting in animal husbandry related business [36], and also in cell-culture experiments [37] under artificial light where also data estimation would help enhance the longevity of the sensor network.

Essentially, *data estimation is aimed at reduction of sensor deployment* in order to enhance the energy life span of the sensor network. The energy conservation strategy however admits the need for *data availability* and aims at achieving *data estimation* as a technique to **substitute** *data acquisition*. The DEPM technique developed in the present thesis is designed for the Continuous Data Delivery Model, mentioned in Chapter II.

Naturally, the success of the strategy depends in a very sensitive manner on the reliability of the estimation technique. Most techniques depend on 'in network aggregation and estimations of statistical fluctuations of the data parameters to determine the estimates'. Some methods of data estimation are reviewed next.

IV.1 Power saving using physical method (DEPM) to estimate information

P. Dash et al. [38] have studied, using physical laws for data estimation, approximate values of land surface temperature and emissivity from passive sensor data. .Land

Surface Temperature (LST) is the temperature measured at the Earth's surface and is regarded as its skin temperature.

Essentially, this paper makes use of well-known laws of Physics to estimate the Land Surface Temperature realistically. Calibration has been employed as a generalized parameter for data estimation in sensor networks [39] to be interfaced with devices that do not already have one. This technique allows one to calibrate general purpose devices for specialized tasks and provides an additional advantage in enabling calibration of software so that one can leverage the redundancy and distributed computational power of sensor networks to have the network calibrate itself. This feature makes it feasible to calibrate even very large networks.

The reduction in redundancy that results from the application of this method offers energy conservation prospects.

IV.2 Linear Response of Physical Parameters and Superposition Principle – E*nergy conservation in WSN using ISL of EMR*.

In many applications, it is not necessary for users to obtain the accurate sensing value at all the time. A scheme that provides approximate answers may offer an opportunity to prolong sensor network lifetime efficiently. By developing an algorithm that enables a few active sensors estimate the data that can be gathered by all other

sensors, within a tolerance limit, we achieve extensive energy conservation by permitting a large number of sensors to sleep.

In this Section is presented a novel energy saving mechanism. The present technique's strategy is aimed at obtaining data estimation using fundamental laws of physics. The primary concept employed in this endeavor is the recognition of the fact that when data are reliably estimated, then the same need not be communicated nor acquired by a sensor. Thus, the sensors which would be otherwise required to obtain the data (that is now reliably estimated) can be put to 'sleep' and a large amount of energy consumption is thus avoided.

Given a region **R** in which a set of N sensors **S** = $\{s_1, s_2,, \ldots\ldots, s_N\}$ gather data on a physical parameter, a working scheme ***WS*** is derived for **S** such that:

1) For each sensor s_i, its returned value V_e deviates from the real value V of the parameter that is sensed by no more than ε, that is, $|V - V_e| \leq \varepsilon$.
2) The energy consumption among all the sensors is optimally minimized, thus maximizing the lifetime of the sensor network.
3) Physical laws are used in the present formalism to achieve energy conservation.

To conserve energy, some sensors in a sensor network can be in sleep mode and only a subset of the sensors is responsible for sensing and communication. Sensors work in rounds (Figure 4.2).

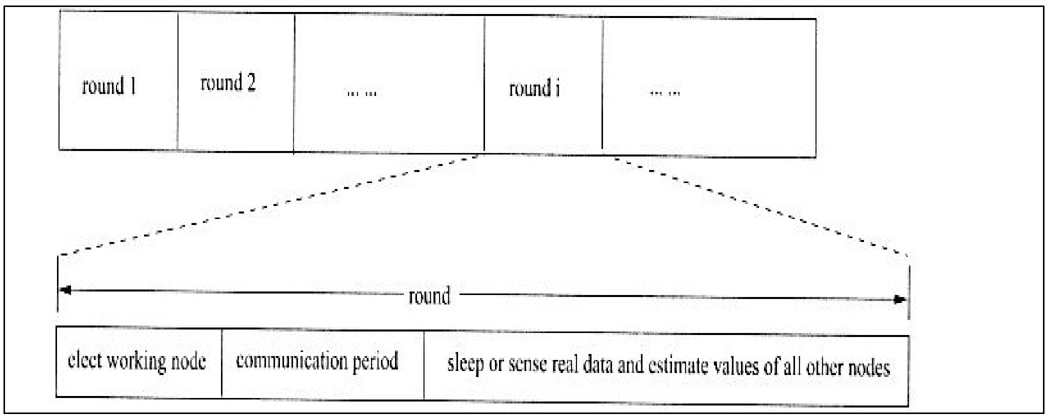

Figure 4.2: Schematic Representation of 'Rounds' in Sensor networks

In each round, a subset of the sensor nodes is elected to serve as the working nodes. The working nodes are responsible for sensing and estimating values of other sensors. Other sensors can switch to sleep mode to save energy.

<u>In the present scheme, basic laws of physics are employed to estimate data</u>. This is achieved by exploiting the principle of superposition of the physical parameter that is to be sensed. Since the principle of superposition is a very common principle in physics and is obeyed by a large number of physical quantities, the present technique will have wide applicability. Furthermore, the linear superposition offers tremendous advantage in that it lends itself to an analysis based on solving linear inhomogeneous

algebraic equations that enables us to deploy a small constant number of sensors amongst a large number of available sensors thereby conserving battery power of the sensor network.

Essentially, the problem is one of determining a physical quantity at a field point when the value at the field point is the result of linear superposition of that quantity and is produced by multiple sources. The present technique seeks to eliminate the need of deploying any more sensors than the constant number that is equal to the number of sources and allowing all the extra sensors to sleep. This method is able to predict very accurately with practically no uncertainty the value of the physical quantity under observation at the locations of the sleeping node. By activating one of the sleeping nodes, one can carry out an actual sensory measurement at that location and verify the prediction of the physical model. After such verification, the algorithm enables, as long as source properties remain invariant, the prediction of the physical quantity at an infinite number of locations within the region R and makes it redundant to deploy sensors at these new locations. This technique thus achieves enormous energy conservation by exploiting the principle of linear superposition by solving a set of algebraic linear inhomogeneous equations thereby providing accurate physical estimates of the physical quantity at an infinite number of points in the region without having to consume energy in activating additional sensors in the region.

To define and illustrate the functioning of the algorithm, consider a total of N sensor nodes and M sources (M << N) of light. Each of the light sensors register an amount of light intensity I_k at the sensor node S_k for every value of k Є [1, N] in the system.

The base station needs to determine the power radiated by each source of light from the measurements of light intensities measured by sensors.

DEPM operates in two modes: (a) Dynamic and (b) Static.

The DYNAMIC mode of DEPM is employed when the power radiated by the M sources is not known and needs to be measured by active sensors. DEPM provides energy conservation by accurately estimating the power of the M sources by employing only M << N active nodes. Toward this goal, DEPM exploits the principle of linear superposition and provides solutions by addressing a set of linear algebraic inhomogeneous equations. Energy minimization is achieved by requiring only a constant minimal number M out of the available N sensors to be activated to determine the power radiated by the M sources. In each round, the DEPM algorithm solves the set of linear inhomogeneous equations thus providing the accurate reliable values of the light power P radiated by the M light sources. The STATIC mode of DEPM is employed when (a) the power radiated by the sources is rest determined by carrying out sensor measurements in the DYNAMIC mode, and (b) when it is known that the power radiated by the light sources is time-invariant as is often the case. In

the STATIC problem, no sensor is required to be activated, except to verify the DEPM prediction, even as the DEPM algorithm solves the inverse problem and estimates with complete accuracy the values of light intensity distribution at an infinite set of point locations in the region R without consuming energy in activating any sensor at all.

DYNAMIC DEPM Algorithm:

In each execution round, three tasks are processed:

(i) At the beginning, M out of N sensor nodes are elected to function as active nodes by using a random algorithm which ensures that battery is conserved in all of the N sensors optimally.

(ii) The light intensity I_k data, for k ε [1,M], sensed by the M active nodes are sent to the base station.

(iii) The base station computes the values of the *light power luminosity* P_L radiated by each of the l^{th} light source using the DEPM dynamic alogorithm (using the inverse square law for light intensity), explained below.

If the j^{th} light source alone were switched on, the rest of the (M-1) light sources being switched off, then the light intensity I_k measured by the k^{th} active sensor is related to the power P_j of the j^{th} light source by the well-known inverse square law:

$$I_k = \frac{P_j}{4\pi d^2(s_k, l_j)} \tag{1}$$

where $d(s_k, l_j)$ is the distance between the j^{th} light source and the k^{th} sensor.

The above mathematical relation is essentially the INVERSE SQUARE LAW of the ELECTRO-MAGNETIC RADIATION that was discussed in Section I.3.

Now, if all the M light sources are switched on, one requires a minimum of M sensors to uniquely determine the light powers of each of the M light sources. Since the light power luminosity of the M light sources would change with time, one would need to carry out such measurements over a large period of time. However, if the same sensors are used over this large period, they would run out of their battery power supply. DEPM addresses this issue by randomly selecting the M sensors from a set of $N \geq M$ to be activated for this purpose; and permitting all the remaining sensors to sleep and conserve their energy.

Thus, at the beginning of each round, DEPM elects M nodes as active working nodes. For the sake of balancing the sensors' energy, the active nodes are always selected randomly from the subset of sensors that have residual energy that is higher than the average energy per sensor in the entire network. The selected active nodes then sense the light intensity I_k of light at each k^{th} sensor node and communicate the recorded values to the base station.

$$I_1 = \frac{P_1}{4\pi d^2(s_1, l_1)} + \frac{P_2}{4\pi d^2(s_1, l_2)} + ... + \frac{P_M}{4\pi d^2(s_1, l_M)}$$

$$I_2 = \frac{P_1}{4\pi d^2(s_2, l_1)} + \frac{P_2}{4\pi d^2(s_2, l_2)} + ... + \frac{P_M}{4\pi d^2(s_2, l_M)}$$

$$\cdots$$

$$\cdots$$

$$\cdots$$

$$I_M = \frac{P_1}{4\pi d^2(s_M, l_1)} + \frac{P_2}{4\pi d^2(s_M, l_2)} + ... + \frac{P_M}{4\pi d^2(s_M, l_M)} \tag{2}$$

Since the light intensity I_k at the k^{th} sensor obeys the principle of superposition with respect to light reaching that sensor from each of the M number of light sources, we have:

$$I_k = \sum_{j=1}^{M} \frac{P_j}{4\pi d^2(s_k, l_j)} = \sum_{j=1}^{M} a_{kj} \; P_j, \tag{3}$$

where

$$a_{kj} = \frac{1}{4\pi d^2(s_k, l_j)}. \tag{4}$$

Equations (3) represent a family of linear inhomogeneous algebraic equations in which the coefficients a_{kj} are known from the geometrical arrangements of the sensor network and the locations of the M light sources. The inhomogeneous linear equations can be solved using well-known techniques [40].

These equations can be written in a matrix form:

$$\begin{bmatrix} a_{1,1} & a_{1,2} & \cdots\cdots & a_{1,k} & \cdots\cdots & a_{1,M} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ a_{k,1} & a_{k,2} & \cdots\cdots & a_{k,k} & \cdots\cdots & a_{k,M} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ a_{M,1} & a_{M,2} & \cdots\cdots & a_{M,k} & \cdots\cdots & a_{M,M} \end{bmatrix} \begin{bmatrix} P_1 \\ P_2 \\ \cdots\cdots \\ P_k \\ \cdots\cdots \\ P_M \end{bmatrix} = \begin{bmatrix} I_1 \\ I_2 \\ \cdots\cdots \\ I_k \\ \cdots\cdots \\ I_M \end{bmatrix} \tag{5}$$

i.e.,

$$\alpha\ \pi = \iota, \tag{6}$$

where

$$\alpha = \begin{bmatrix} a_{1,1} & a_{1,2} & \cdots\cdots & a_{1,k} & \cdots\cdots & a_{1,M} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ a_{k,1} & a_{k,2} & \cdots\cdots & a_{k,k} & \cdots\cdots & a_{k,M} \\ \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots & \cdots\cdots \\ a_{M,1} & a_{M,2} & \cdots\cdots & a_{M,k} & \cdots\cdots & a_{M,M} \end{bmatrix}, \tag{7}$$

$$\text{the matrix } \pi = \begin{bmatrix} P_1 \\ P_2 \\ \cdots\cdots \\ P_k \\ \cdots\cdots \\ P_M \end{bmatrix}, \text{ and the matrix } \iota = \begin{bmatrix} I_1 \\ I_2 \\ \cdots\cdots \\ I_k \\ \cdots\cdots \\ I_M \end{bmatrix}. \tag{8}$$

We note that the matrix α is determined entirely by geometrical arrangement and is completely independent of the light source and the sensor properties.

The solution to this system of equations is:

$$\pi = \alpha^{-1}\iota, \qquad (9)$$

i.e.,

$$P_k = \sum_{j=1}^{M} .\alpha_{kj}^{-1}\ \iota_j\ , \qquad (10)$$

where α^{-1} is the inverse of the matrix α. Clearly, this method would fail if the determinant of the matrix α vanishes, i.e., if

$$|\alpha| = 0. \qquad (11)$$

Thus, from the values of the light intensities sensed by the set of M active sensors, DEPM dynamic algorithm determines the power radiated by each of the M light sources.

IV.3 COMPARITIVE DISCUSSION

1) Energy saving is achieved by allowing all of the (N-M) sensors to sleep.
2) The estimate of the physical quantity of interest, namely the power P radiated by each of the M number of light sources is obtained using physical laws.

The Dynamic DEPM technique offers itself as a very powerful algorithm to solve the inverse problem when it is known that the power radiated by each of the light sources is not changing, as is often the case, and it is of importance to know the distribution of intensity of light at a large number of point-locations in the region illuminated by the M light sources.

Such problems are of interest in very many different areas, such as in the determination of light intensity distribution in a sports arena where games are played under artificial light sources of constant power, and in horticulture experiments [34,35] in which cultivation of some vegetation is sought under artificial light from a set of constant-power sources. Likewise, a cell-culture experiment [36] under controlled light intensity environment is another example of a situation where the Static DEPM model can be extremely valuable.

To solve such problems, the DEPM inverse algorithm is to be used, treating the matrix $\boldsymbol{\pi}$ as known and determining the intensity matrix $\boldsymbol{\iota}$ for any set of M point-locations whose coordinates alone determine the corresponding matrix $\boldsymbol{\alpha}$. Thus, for a predetermined matrix $\boldsymbol{\pi}$ and for a set of arbitrary M number of locations whose coordinates alone determine the required matrix, the DEPM static algorithm solves the matrix relation: $\alpha\pi = \iota$, thereby giving the values of the light intensities at a set of M arbitrary locations whose coordinates alone need to be provided as input for the DEPM static algorithm. Not a single sensor needs to be

activated at this set of M locations thus providing reliable data estimation that substitutes data acquisition thereby conserving battery power of the sensor network. Of course, some of the sensors can be activated to verify the prediction of the DEPM static algorithm, and this is a tremendous advantage that lends itself as a tool to check reliability of the model. Thus one achieves data estimation with regard to light intensity distribution at arbitrary locations (x,y,z) without using actual sensors being activated at these locations, and using a method that is completely based on physical laws.

While physical laws have been used in some of the technologies mentioned above to govern sensor mechanisms, in the DEPM technique proposed in the present work, it is for the first time that physical laws are employed in a direct energy saving strategy aimed at data estimation. Most other methods rely on some form of temporal and/or spatial correlations and/or data filtration for data estimation, whereas in the present work well-established physical laws that are known to be correct with extremely high accuracy are used directly in the network plan to achieve minimization of energy consumption which is the primary challenge in WSN technology.

In the next Chapter, an experimental set-up is described that demonstrates a successful implementation of the DEPM technique.

V. Experimental Analysis

In this Chapter is presented an experimental demonstration of the physical methodology developed to conserve energy using physical laws for data estimation. The experimental set up is aimed at implementing the DEPM technique developed in this thesis in a real time scenario in the laboratory using commercial sensors and light sources.

V.1 Experimental Set-up

The experiment was carried out in a 25’x50’ laboratory in which the only light sources were two commercial light sources, apart from minimal background electromagnetic thermal radiation that is emitted by any and every object which is at any finite temperature. This background radiation cannot be cut off, but one can always use filters on sensors that will eliminate this extraneous electromagnetic radiation.

Crossbow’s TelosB Mote TPR2420 Sensors, shown in Figure 5.1, was employed in the experiments performed to test the DEPM algorithm. Commercial Light Sources were used to carry out the experiments. Two light sources L_1 and L_2 and a set of twenty TelosB sensors were used. The two light sources were suspended from the ceiling and the sensors were placed on the floor in the laboratory of size 25’x50’ as shown in the Figures 5.2 through 5.6.

Distances between each of the two light sources and each of the twenty TelosB sensors were measured carefully (Figure 5.7). These distances are reported in Table 5.1.

Figure 5.1 Crossbow's TelosB Mote TPR2420 Sensor

Fig.5.2: The light source

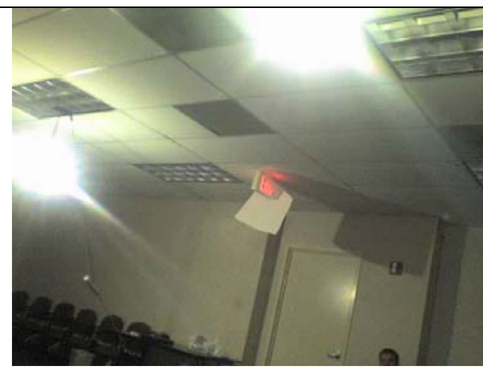

Fig.5.3: The light sources were suspended from the ceiling

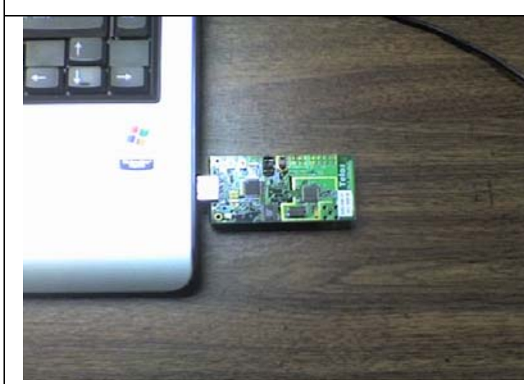

Fig.5.4: Computerized Analysis

Fig.5.5: Computerized Analysis

Figure 5.6: The 20 TelosB sensors were laid on the floor

Figure 5.7: Distances between each of the twenty sensors and each of the two light sources were measured carefully.

$D[S_i,L_1]$ $i=1,2,3,\ldots.,20$	$D[S_j,L_2]$ $j=1,2,3,\ldots.,20$
r[1][1] = 272.0	r[1][2] = 435.0
r[2][1] = 216.0	r[2][2] = 413.0
r[3][1] = 211.0	r[3][2] = 341.0
r[4][1] = 208.0	r[4][2] = 446.0
r[5][1] = 233.0	r[5][2] = 331.0
r[6][1] = 276.0	r[6][2] = 338.0
r[7][1] = 224.0	r[7][2] = 324.0
r[8][1] = 254.0	r[8][2] = 303.0
r[9][1] = 304.0	r[9][2] = 293.0
r[10][1] = 235.0	r[10][2] = 293.0
r[11][1] = 330.0	r[11][2] = 254.0
r[12][1] = 272.0	r[12][2] = 256.0
r[13][1] = 271.0	r[13][2] = 255.0
r[14][1] = 313.0	r[14][2] = 231.0
r[15][1] = 382.0	r[15][2] = 195.0
r[16][1] = 415.0	r[16][2] = 221.0
r[17][1] = 380.0	r[17][2] = 213.0
r[18][1] = 441.0	r[18][2] = 201.0
r[19][1] = 428.0	r[19][2] = 224.0
r[20][1] = 337.0	r[20][2] = 215.0

Table 5.1: Actual Distances Measured (in centimeters) between the twenty Sensors and the two Light Sources.

V.2 Simulation Results

Described below are the results of three different experiments performed under three different lighting conditions.

Experiment No. 1:

In the first experiment, the two light sources were kept continuously 'ON' for a period of 40 minutes. Sensor values were registered and the DEPM algorithm described in Chapter 4 was implemented. The results are shown in Figure 5.8 for 3 different cases corresponding to the minimum value of the determinant $|\alpha|_{minimum} = \delta$. The method is expected to work when $\delta > 0$. The figures show that the percentage error diminishes rapidly as δ is increased, and is ~0.5% for δ =0.05.

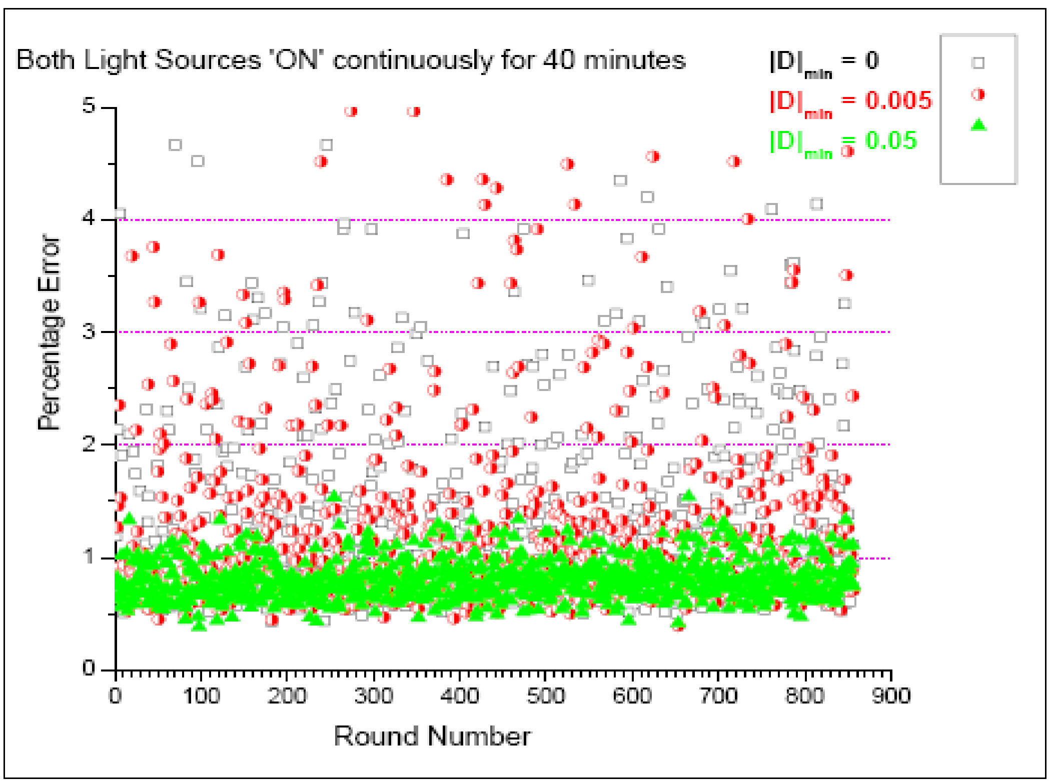

Figure 5.8: Scatter of percentage errors in the experiment performed over 40 minutes with both the Light Sources continuously 'ON'. The method is expected to work when the $|D|_{minimum}$ is not zero, as is clearly seen in the results.

Statistical analysis on Experiment No. 1 is reported in Table 5.2.

Set 1: Both Light Sources 'ON' continuously for 40 minutes	Setting - 1	Setting - 2	Setting - 3
Coefficient of Variation	0.796874	1.413661	17.10685
$\lvert\text{Determinant}\rvert_{\text{Minimum}}$ (δ)	0	0.005	0.05
Average % Error	3.66	1.32	0.86

Table 5.2: Statistics on error analysis on the experiment when both light sources L_1 and L_2 were kept 'ON'

<u>Experiment No. 2:</u>

In the experiment for 'Set 2', the light sources L_1 and L_2 were turned 'ON' and 'OFF' according to a fixed pattern, described in Table 5.3, over 5-minutes intervals over a total period of 30 minutes:

Time Interval in Minutes	Light Source L_1	Light Source L_2
00-05	On	On
05-10	Off	On
10-15	Off	Off
15-20	On	Off
20-25	On	On
25-30	Off	Off

Table 5.3: Schedule for 'Set 2 experiment' in which the Light Sources L1 and L2 were turned 'ON' and 'OFF'.

Sensor values were registered and the DEPM algorithm described in Chapter 4 was implemented. The results are shown in Figure 5.9 for 3 different cases corresponding to the minimum value of the determinant $|\alpha|_{minimum} = \delta$. The method is expected to work when $\delta > 0$. The figures show that the percentage error diminishes rapidly as δ is increased, and is ~0.5% for $\delta = 0.05$.

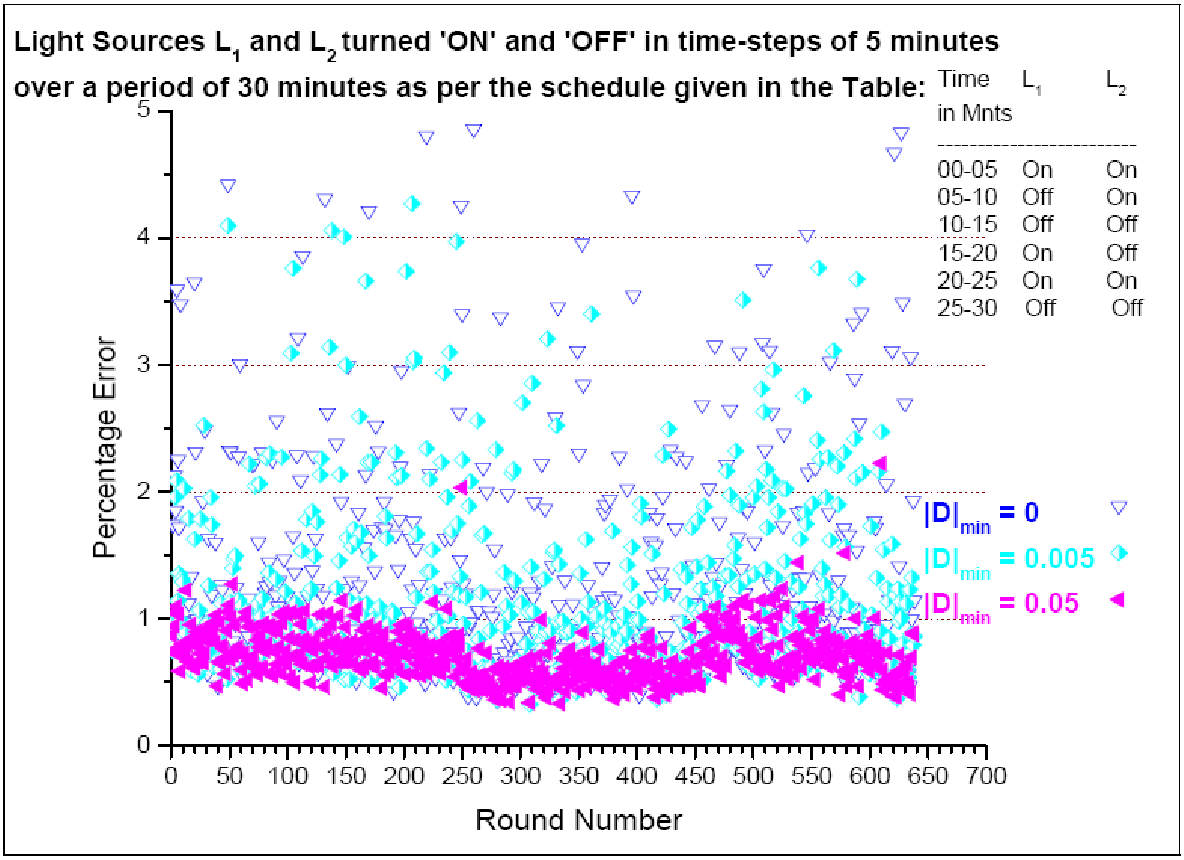

Figure 5.9: Scatter of percentage errors in the experiment performed over 30 minutes during which the Light Sources L_1 and L_2 were turned 'ON' and 'OFF' as per the schedule given above. The method is expected to work when the |D|minimum is not zero, as is clearly seen in the results.

Statistical analysis on Experiment No. 2 is reported in Table 5.4.

Set 2: Light Sources S_1 & S_2 turned 'ON' and 'Off' as per the schedule described above.	Setting - 1	Setting - 2	Setting - 3
Coefficient of Variation	0.710729	1.054341	12.44866
$\lvert\text{Determinant}\rvert_{\text{Minimum}}$ (δ)	0	0.005	0.05
Average % Error	5.47	1.15	0.71

Table 5.4: Statistics on error analysis on the experiment when the light sources L_1 and L_2 were turned 'ON' and 'OFF' as per the schedule given above.

<u>Experiment No. 3:</u>

In the experiment for 'Set 3', the light sources L_1 and L_2 were turned 'ON' and 'OFF' *randomly* over a total period of 20 minutes. Sensor values were registered and the DEPM algorithm described in Chapter 4 was implemented. The results are shown in Figure 5.10 for 3 different cases corresponding to the minimum value of the determinant $|\alpha|_{\text{minimum}} = \delta$. The method is expected to work when $\delta > 0$. The figures show that the percentage error diminishes rapidly as δ is increased, and is ~0.5% for $\delta = 0.05$.

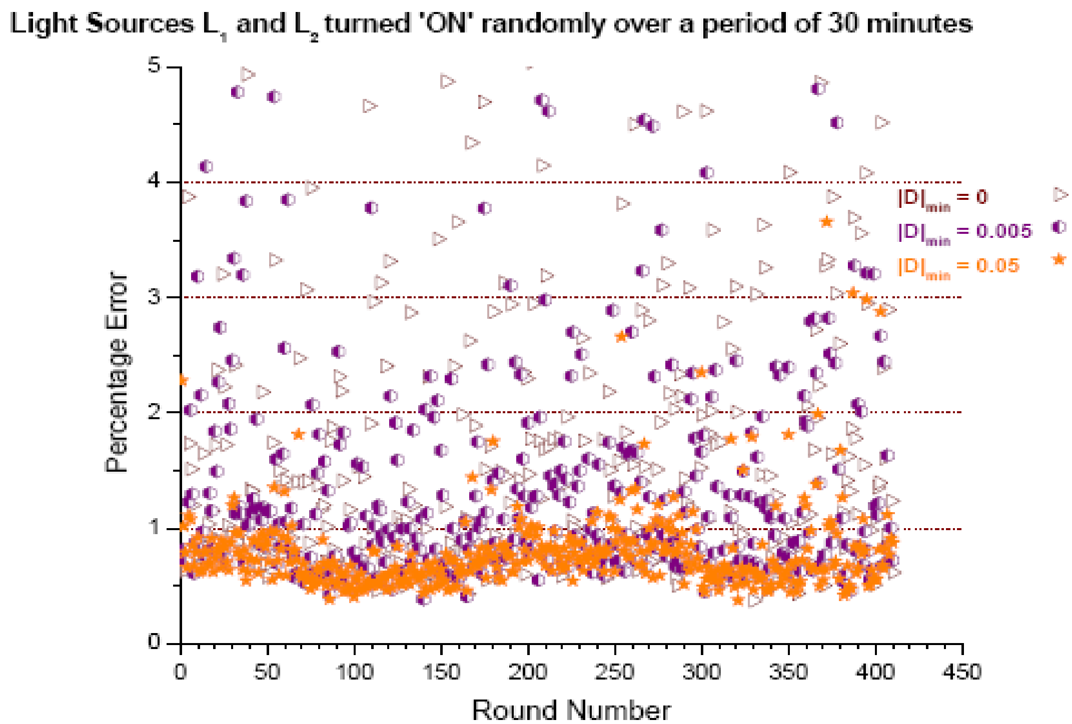

Figure 5.10: Scatter of percentage errors in the experiment performed over 30 minutes with the Light Sources L1 and L2 turned 'ON' randomly. The method is expected to work when the |D|minimum is not zero, as is clearly seen in the results.

Statistical analysis on Experiment No. 3 is reported in Table 5.5.

Set 3: Light Sources S_1 & S_2 turned 'ON' and 'OFF' *randomly*	Setting - 1	Setting - 2	Setting - 3
Coefficient of Variation	0.588899	0.654268	7.84494
$\lvert$Determinant$\rvert_{\text{Minimum}}$ (δ)	0	0.005	0.05
Average % Error	5.79	1.39	0.79

Table 5.5: Statistics on error analysis on the experiment when the light sources L_1 and L_2 were turned 'ON' and 'OFF' randomly.

To conserve the sensor network energy, in this scheme is proposed that only a few nodes are selected to work, and the other nodes are set to sleep. The data sensed by sleeping node are estimated by DEPM. The DEPM technique utilizes the physical laws to estimate data. Since the `principle of superposition' on which DEPM is based is a very common principle in physics and is obeyed by a large number of physical quantities, the present technique will have a very wide applicability. Furthermore, the linear superposition principle offers tremendous advantage in that it lends itself to an analysis based on solving linear inhomogeneous algebraic equations that enables us to deploy a rather small constant number of sensors from amongst a large number of available sensors, thereby conserving much of the battery power of the sensor network.

Details of the experimental setup can also be found at:
http://qubit.cs.gsu.edu/~wdeshmukh1/8999/sensor.html

VI. Summary and Conclusions

In this concluding Chapter, a brief summary of the contents of all the earlier five chapters is provided, and conclusions are consolidated. In the last section is provided a brief discussion on scope for future work and comments on challenges ahead.

VI.1 Summary and Conclusions

In Chapter I are briefly reviewed for the sake of providing a general introduction, perspectives in remote sensing networks and physical constraints in setting up network topology. An introduction to sensors that detect and measure the intensity of electromagnetic radiation is provided.

In Chapter II, certain characteristic parameters that constitute essential features of wireless sensor networks are discussed along with well known 'network models'.

In Chapter III, well-established related techniques of data management and routing strategies, and data filtering methods that are commonly used to achieve minimization of energy consumption are briefly reviewed.

In Chapter IV is described the novel technique developed in the present work aimed as an energy saving strategy wherein data estimation is used to substitute data

acquisition for energy conservation, but unlike earlier efforts in this direction, the strategy is based on direct application of well established physical laws. The new method that is developed is called DEPM: Data Estimation using Physical Model. In DEPM, a scheme is proposed where only a few nodes are selected to work, and the other nodes are set to sleep. The data sensed by sleeping node are estimated by DEPM. The `principle of superposition' on which DEPM is based is a very common principle in physics and is obeyed by a large number of physical quantities. The present technique therefore will have a very wide applicability. Furthermore, the linear superposition principle offers tremendous advantage in that it lends itself to an analysis based on solving linear inhomogeneous algebraic equations that enables us to deploy a rather small constant number of sensors from amongst a large number of available sensors, thereby conserving much of the battery power of the sensor network.

In Chapter V is reported a detailed analysis of several different experiments carried out in the laboratory using commercial sensors to test the DEPM. Results demonstrate that the DEPM algorithm is quite robust and offers itself as a very reliable energy saving strategy in wireless sensor networks.

VI.2 Scope for Further Work; Challenges ahead

The experiments reported in this thesis have been performed with commercial sensors. The DEPM will get increasingly useful if the background radiation is filtered out; as can be easily achieved if the sensor devices are capped by appropriate filters. The DEPM energy saving strategy therefore offers encouraging promise as its reliability can be significantly improved by mounting filters on sensors to eliminate noise due to background radiation. Technology improvisation in sensor accessories in the future may thus include development of filters that will make sensors more

specific with regard to the response to the stimuli they are aimed at detecting and measuring.

A possible application of DEPM can be, for example, in charged particle (such as electrons, positrons, alpha particles etc.) accelerators in which magnetic lenses are employed to make the charged particles bend the direction of motion of the charged particles. The magnetic field at various points inside the accelerators needs to be carefully mapped for the magnetic lenses to perform correctly; it is challenging to do so since mapping the magnetic fields at a very large number of field points is not experimentally trivial by way of installing magnetic sensors inside the particle accelerators. The magnetic field at a point due to a current is governed through the Biot-Savart law, and it obeys the principle of superposition on which the DEPM technique is based.

Essentially, the Biot-Savart law can be written for an infinitesimal magnetic field generated by a current in an elemental current-carrying conductor, shown in Figure 6.1.

Magnetic field of a current element

$$d\vec{B} = \frac{\mu_0 I d\vec{L} \, x \, \vec{1}_r}{4\pi r^2}$$

where

$d\vec{L}$ = infinitesmal length of conductor carrying electric current I

$\vec{1}_r$ = unit vector to specify the direction of the the vector distance r from the current to the field point.

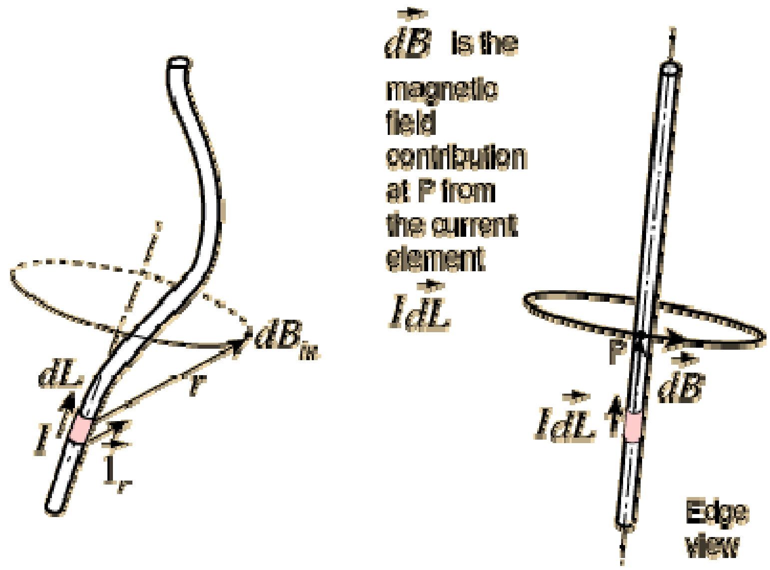

Figure 6.1: Infinitesimal magnetic field generated by an electric current in an elemental current-carrying conductor [41].

As can be easily seen, the Biot-Savart Law relates magnetic fields to the currents which are their sources just as the Coulomb's law relates electric fields to the point charges which are their sources. Finding the magnetic field resulting from a current distribution involves the determination of a vector product, and is inherently a calculus problem when the distance from the current to the field point is continuously changing. The magnetic field at a field point however obeys the principle of linear superposition on the basis of which the DEPM technique developed in the present thesis operates. DEPM can therefore provide applications in such situations since it has for its platform the principle of linear superposition of a physical quantity that can be used to set up a system of linear inhomogeneous algebraic equations. A very large number of physical situations therefore lend themselves to DEPM application since the principle of linear superposition is obeyed by a very large number of physical quantities whose values need to be determined using sensor networks.

References

[1] http://eosweb.larc.nasa.gov/EDDOCS/Wavelengths_for_Colors.html

[2] http://en.wikipedia.org/wiki/Thermometer

[3] http://www.scienceandsociety.co.uk/results.asp?image =10303128&wwwflag=2&%20 imagepos=5

[4] http://www.ag.ndsu.edu/pubs/ageng/gis/ae1262w.htm

[5] http://w3.antd.nist.gov/wctg/smartsensors/sensornetworks.html

[6] Abhay Joshi, Rajan Batta and Rakesh Nagi
'Ad hoc sensor network topology design for distributed fusion: A mathematical programming approach'
http://www.fusion2004.foi.se/papers/IF04-0836.pdf

[7] Malik Tubaishat and Sanjay Madria: 'Sensor networks: an overview'
20 0278-6648/03/$17.00 © 2003 IEEE IEEE POTENTIALS
http://ieeexplore.ieee.org/iel5/45/26953/01197877.pdf?arnumber=1197877

[8] Walt Pastorius
Vision Sensors & Systems For Hostile Environments
http://www.machinevisiononline.org/public/articles/Sensors_for_Hostile_Environments.pdf

[9] Inverse Square law of Light
http://hyperphysics.phy-astr.gsu.edu/hbase/vision/isql.html

[10] http://news.com.com/FAQ+Forty+years+of+Moores+Law/2100-1006_3-5647824.html?tag=st.num

[11] Sameer Tilak, Nael B., Abu-Ghazaleh, and Wendi Heinzelman
'A Taxonomy of Wireless Micro-Sensor Network Models'
ACM SIGMOBILE Mobile Computing and Communications Review archive
Volume 6 , Issue 2 (April 2002) Pages: 28 - 36

[12] http://www.cs.binghamton.edu/~sameer/pubs/wcnc02-draft.pdf

[13] Hari Rangarajan J . J . Garcia-Luna-Aceves
Reliable Data Delivery in Event-Driven Wireless Sensor Networks *
0-7803-8623-x104/$20.00 02004 IEEE
http://ieeexplore.ieee.org/iel5/9388/29803/01358410.pdf

[14] Project Report, by Mei Li, Yuexin Liu,
Pennsylvania State University

[15] Stephanie Lindsey, Cauligi Raghavendra and K. M. Sivalingam,
IEEE Transactions on Parallel and Distributed Systems, special issue on
Mobile Computing, April 2002

[16] David Chu, Amol Deshpande, Joseph M. Hellerstein, Wei Hong;
Proceedings of the 22nd International Conference on Data Engineering, 2006.
ICDE '06.

[17] Himanshu Gupta, Vishnu Navda, Samir R. Das, Vishal Chowdhary

Proceedings of the 6th ACM international symposium on Mobile ad hoc networking and computing (MobiHoc) 2005, Urbana-Champaign, IL, USA May 25 - 27, 2005.

[18] Adam Silberstein, Rebecca Braynard & Jun Yang
Proceedings of the 2006 ACM SIGMOD International Conference on Management of Data Chicago, IL, USA

[19] Samuel Madden, Michael J. Franklin, Joseph Hellerstein and Wei Hong
Proceedings of the Fifth Symposium on Operating Systems Design and implementation (OSDI'02), December 9-11,2002, Boston, MA, USA.

[20] Mohamed Younis, Anugeetha Kunjithapatham and Kemal Akkaya,
IEEE Symposium on Computers and Communications (ISCC)'2003

[21] Yong Yao, Johannes Gehrke,
Proceedings of 1st Biennial Conference on Innovative Data Systems Research (CIDR 2003), Jan 2003, Asilomar, CA. Cornell University

[22] Sylvia Ratnasamy and Brad Karp,
First ACM International Workshop on Wireless Sensor Networks and Applications (WSNA 2002), Atlanta, GA, September, 2002. UC Berkeley;

[23] Konstantinos Kalpakis, Koustuv Dasgupta, and Parag Namjoshi,.
In the Proceedings of the 2002 IEEE International Conference on Networking (ICN'02), Atlanta, Georgia, August 26-29, 2002. pp. 685-696.

[24] Marc Lee and Vincent W.S. Wong (University of British Columbia, Canada)
IEEE GLOBECOM 2005 Proceedings

[25] Dragan Petrovic, Rahul C. Shah, Kannan Ramchandran, Jan Rabaey
Proceedings of the 2003 IEEE Sensor Network Protocols and Applications, May 2003.

[26] Suman Nath, Phillip B. Gibbons, Srinivasan Seshan & Zachary R. Anderson
Proceedings of SenSys'2004

[27] Amit Manjhi, Suman Nath & Phillip B. Gibbons
In Proceedings of the 2005 ACM SIGMOD International Conference on Management of Data, June 2005.

[28] Deepak Ganesan, Ramesh Govindan, Scott Shenker & Deborah Estrin
ACM Mobile Computing & Communications Review, Vol.5, No.4, Oct'2001.

[29] David Chu, Amol Deshpande, Joseph M. Hellerstein and Wei Hong. Approximate Data Collection in Sensor Networks using Probabilistic Models, Proceedings of the 2nd International Conference on Data Engineering (ICDE, 2006).

[30] Ankur Jain, Edward Y. Chang and Yuan-fang Wang. Adaptive stream resource management using Kalman Filters, In SIGMOD 2004.

[31] Daniel de O. Cunha, Rafael P. Laufer, Igor M. Moraes, Marco D. D. Bicudo, Pedro B. Velloso, and Otto Carlos M. B. Duarte
Bio-Inspired Field Estimation withWireless Sensor Networks.
http://www.gta.ufrj.br/ftp/gta/TechRe

[32] Loukas Lazos, Radha Poovendran and Srdjan Capkun Rope: Robust Position Estimation In Wireless Sensor Networks

http://www.ee.washington.edu/research/nsl/papers/IPSN05.pdf#search=%22 ROPE%20Loukas%20La

[33] P. Bose, E. Kransakis, P. Morin, and Y.Tang.
Bounds for Frequency Estimation of Packet Streams Proceedings in Informatics
http://cg.scs.carleton.ca/~morin/publications/tra¢ c/streaming-sirocco.ps.gz

[34] Runckle, E.S. and Heins, R.D. 'Manipulating the light environment to control flowering and morphogenesis or herbaceous plants.
ISHS Acta Horticulturae 711, V International Symposium on Artifcial Lighting in Horticulture, 30 June 2006, Lillehammer, Norway

[35] http://www.avantes.com/Applications/HortiSpec.htm

[36] http://www.mass.gov/agr/animalhealth/petshops/330%20CMR%2012.00%20 Final%20no%20red%2

[37] http://www.springerlink.com/content/x5w37438200126q2/13

[38] P. Dash et. al.
Land Surface Temperature and Emissivity Estimation from Passive Sensor Data: Theory and Practice.Current Trends, International Journal of Remote Sensing, 2002, vol. 23, no. 13, 2563.2594

[39] KaminWhitehouse and David Culler,
Calibration as Parameter Estimation in Sensor Networks. WSNA.02, September 28, 2002, Atlanta, Georgia, USA.

[40] G.B.Arfken and H.J.Weber,

Mathematical Methods for Physicists., 5th Edition,

page 166, (Academic Press) 14

[41] http://hyperphysics.phy-astr.gsu.edu/hbase/magnetic/biosav.html