Progress In Electromagnetics Research M, Vol. 37, 11–20, 2014

Energy Optimized Wireless Sensor Network for Monitoring inside Buildings: Theoretical Model and Experimental Analysis

Malka N. Halgamuge[1, *], Priyan Mendis[2], Lu Aye[2], and Tuan Ngo[2]

Abstract—Environment monitoring and automatic control of a building is a vital application of wireless sensor network; however, to maximize the network lifetime is a key challenge. The investigation of designing an efficient sensor network that minimizes energy dissipation in a battery of the sensor node, with limited battery power, is a vital consideration for the sensor network lifetime. Battery lifetime greatly affects the overall network communication performance, hence, the careful management of communication distance is very important. In this paper we propose a new model to estimate the mean square distance from the sensor to the cluster head in sensor fields, such as the ones used for monitoring humidity, temperature, light intensity and air quality (CO and CO_2 level), considering three-dimensional building structures. We use experimental datasets of the link quality distribution in an indoor building environment (single storey as well as multi-storey buildings) to investigate the possible building length of the different clusters and the data success rates. We then statistically analysed the data success rate of the experimental datasets using the Wilcoxon Rank Sum test and found that there was no statistically significant difference ($p > 0.05$). Our results show that the clustering is important for the single storey and multi-storey building sensor networks, however, after a certain size of the building it is unimportant. Our results also demonstrate that we can save sensor battery energy, significantly, by optimizing the distance from the sensor to the cluster head, while obtaining a high data success rate. The results over different clusters of sensor networks suggest its applicability for different building sizes. Based on this paper the designers can optimize energy efficiency subject to the required specifications.

1. INTRODUCTION

Building Automation System (BAS) challenges to monitor and have automatic control of the security, lighting, cooling, humidity levels and ventilation systems in a building using the electronic devices network. BAS or any intelligent building system can be used in schools, hospitals, factories, offices and even homes, to enhance the quality of building services and reduce the operation and maintenance costs [1]. Typical functionalities of BAS include the monitoring and controlling of the heating, ventilation, and air conditioning (HVAC) systems, the management of building facilities (such as lighting, safety and security), and automate meter reading. The technology of wireless sensor network (WSN) has been attracting extensive research and development efforts to replace the traditional wired solutions for BAS. The key challenges of integrating WSN to a BAS include characterizing the radio features of BAS environments and fulfilling the requirements of extremely low energy consumption. Medium access control (MAC) protocols, developed for WSN, can be potentially used in BAS systems [1]. Sensor networks consist of many sensor nodes that can be deployed in random positions. Different aspects of sensor networks such as data aggregation and data fusion [2, 3], packet size optimization [4], cluster formation [5, 6], target localization [7], battery management [8] and network protocols [9, 11]

Received 21 April 2014, Accepted 28 May 2014, Scheduled 14 June 2014

* Corresponding author: Malka N. Halgamuge (malka.nisha@unimelb.edu.au).

[1] Department of Electrical and Electronic Engineering, the University of Melbourne, Australia. [2] Department of Infrastructure Engineering, the University of Melbourne, Australia.

are discussed in the literature with respect to crucial energy limitations. It is obvious that wireless sensor networks are highly energy limited systems if they have to function independently from the main power supply, as it is the case for building monitoring systems and alarms. Sensor networks illustrate a remarkable improvement over traditional sensors, however, there are numerous challenges which still need to be overcome. In turn, these depend strongly on power management, therefore, it is crucial to design energy optimized sensor networks that are mostly battery powered. Power management starts with the task of finding a comprehensive energy model, considering all possible sources of energy drainage [12]. We should then investigate methods of estimating sensor network lifetime. Effective power management requires the development of more efficient communication protocols with the existing battery technology. Ultimately, the effective management methods should lead to sensor network design guidelines, capable of prolonging a sensor network's lifetime.

Using cluster-based communication protocols, sensor nodes send their data to the cluster head (CH) which then forwards the data to a sink node or base station [10]. All sensor nodes within the cluster may be identical, however, the CH may have, in some instances, additional features such as more computational power, longer-range radio and location awareness using the Global Positioning System (GPS). Obviously, power management may also depend on the design requirements of the sensor network, generally dictated by an application concerned. Cluster-based sensor systems can be used when the sensor network is fully wireless or hybrid (wireless and wired) with a known sensor location. Networked sensors are used to monitor and control manufacturing processes and are considered as a part of factory automation. Particularly in sensitive industries such as chemical plants, various types of sensors (chemical, temperature and other types) can provide information to control the process. Other common examples of industrial applications include monitoring, lighting, heating, ventilation and air conditioning in large commercial buildings.

In this paper, we developed a new model to estimate the mean square distance from the sensor to the cluster head by considering a three-dimensional building structure. Using the experimental datasets of the link quality distribution in an indoor building environment (single storey as well as multi-storey buildings), we investigated the potential building length of the different clusters and the data success rates. Our results demonstrated that the clustering is vital for both single storey and multi-storey building sensor networks; however, after certain size of the building it is marginal. Our results also showed that there is substantial room for improvement to save the energy dissipation in the battery of a sensor node. In Section 2, we explain some design challenges created by networks performance objectives and in Section 3 we develop a technique to estimate the mean square distance from the sensor to the cluster head. Section 4 explains the simulation and experimental data setup. In Section 5, we show numerical and experimental results and in Section 6 we conclude the paper.

2. DESIGN CHALLENGES POSED BY NETWORK PERFORMANCE OBJECTIVES

In contrast to the cellular type of wireless network designs, where infrastructure costs play a significant role in the design, the node cost is the main hardware cost associated with wireless sensor networks. A sensor network's main energy consumption occurs in sensing, data processing and communications. Minimizing the energy consumption is a primary goal in sensor network designs, and is addressed in [13]. This goal introduces some other design challenges. The nodes can be designed to have sleep periods, and an event may trigger a node to wake up and start processing that information. This, however, can reduce the responsiveness and, therefore, effectiveness of a node due to its possible latency in the waking up process. Nevertheless, if the event is reported rapidly enough, this strategy can still work in applications with a very high sensor density. Scalability is another major challenge in the design of a sensor network with a large number of sensors. In such situations, protocols must involve localized communication and distributed processing, and may support hierarchical sensor network architectures. It is likely that the design involves heterogeneous sensors in the network. A realistic scenario (used later in this work) is to have a small number of nodes with a high computational capacity and high battery power. Another way is a large number of devices with lower computational capacity and low battery power. A key design criterion is to obtain the right proportion of each group of sensors and the proportion of the computational power between the two types of nodes.

The network design can support self-configuration, as they are ad-hoc networks with no central

management. The network should be capable of configuring its own topology, be self-calibrating and be able to coordinate its own inter-node communication. A sensor network deployment is primarily based on the requirements of the coverage and the connectivity needed. Requirements for the coverage will depend on the environment, the quality and the safety of information to be collected. Requirements for connectivity depend on the topology of information routing selected. When deploying a sensor network: the sensor placement, the number of sensors to be placed and the topology of routing information should be considered.

3. ESTIMATION OF THE MEAN SQUARE DISTANCE FROM THE SENSOR TO CH

Let us consider a wireless sensor network with a cluster topology, in which the sensors are grouped into clusters, and each sensor senses data and transmits it to the cluster head. Consider k cluster sensor network assuming that sensors are randomly uniformly distributed where $k \in \{1, 2^3, 3^3, \ldots, j^3\}$ and j is an integer. Using the optimal number of clusters, the network lifetime can be minimized by minimizing energy dissipation of each sensor node. Let a building have length M where $M \in \{1, 2, \ldots, l_M\}$. Sensor networks can allow remote monitoring of sensitive information, which is important for many applications. Ph.D. thesis in [13] has developed a technique to estimate mean square distance for the square area which can be used in two dimensional sensor fields such as battle fields. However, when we consider three dimensional sensor fields such as monitoring temperature control, light intensity or CO_2 in a multi-storey building, the above model is ineffective. Hence, in this section we developed a model to estimate mean square distance from the sensor to the cluster head by considering a three dimensional building structure. The average linear distance from the sensor to the CH, Θ, is given by $\Theta = M/2(k+1)$, as in [14]. When we consider an area with $M \times M$, the area occupied by each cluster is $\approx M^2/k$, where M^2 is the area of the network and k the number of clusters [15]. The distance from the cluster head to any point in the cubic volume is given by

$$\Theta(x, y, z) = \sqrt{\left(x - \frac{M_1}{2}\right)^2 + \left(y - \frac{M_2}{2}\right)^2 + \left(z - \frac{M_3}{2}\right)^2}.$$

When we consider a cube with $M \times M \times M$, the volume which is covered by each cluster is nearly M^3/k. As in [9], we assume that the CH is at the center of mass of its cluster. We acknowledge that the cluster area can be arbitrarily shaped, but for simplicity, we assume that it is a cube. For $k = 1$, assuming sensors are randomly and uniformly distributed over the cubic volume, the mean square distance from a sensor to its CH is given by $E[\Theta] = \int_0^{M_1} \int_0^{M_2} \int_0^{M_3} d(x, y, z)\rho(x, y, z)dxdydz$. This can be written as, $1/M^3 \int_0^M \int_0^M \int_0^M (x - M/2)^2 + (y - M/2)^2 + (z - M/2)^2 dxdydz$, where $\rho(x, y, z)$, $0 \leq x, y, z \leq M$, is the joint probability density function. If sensors are placed uniformly then we have $\rho(x, y, z) = 1/M^3$. The above calculation is for a cubic volume, hence $k = j^3$ where j is an integer. The mean square distance for $j = 1$ ($k = j^3 = 1^3$) cluster is given by $E[\Theta^2] = 1/M^3 \int_0^M \int_0^M [x^3/3 - Mx^2/2 + 3M^2x/4 + y^2x + z^2x - Myx - Mzx]_0^M dydz$. Assuming that this is true for all sides of the selected cubic volume (room) whose mean square distance from a sensor to its CH is given by $E[\Theta^2] = 1/M^3 \int_0^M M^2z/12[5M^2 - 6Mz + 4z^2]_0^M$. The mean square distance for $j = 1$ cluster ($k = j^3 = 1$) is given by $E[\Theta^2] = 1/M^3 \times M^3/12[5M^2 - 6Mz + 4z^2]_0^M$, $E[\Theta^2] = M^2/4$. Similarly, the mean square distance for $j = 2$ cluster ($k = j^3 = 8$) is given by $E[\Theta^2] = 8/M^3 \int_0^{M/2} \int_0^{M/2} \int_0^{M/2} (x - M/2\sqrt{4})^2 + (y - M/2\sqrt{4})^2 + (z - M/2\sqrt{4})^2 dxdydz$, and the mean square distance for $j = 3$ cluster ($k = j^3 = 27$) is given by $E[\Theta^2] = 27/M^3 \int_0^{M/3} \int_0^{M/2} \int_0^{M/3} (x - M/2\sqrt{9})^2 + (y - M/2\sqrt{9})^2 + (z - M/2\sqrt{9})^2 dxdydz$.

The mean square distance for k cluster ($k = j^3$) (as in Figure 1) can be found by solving

$$E[\Theta^2] = \frac{k}{M^3} \int_0^{\frac{M}{\sqrt{k}}} \int_0^{\frac{M}{\sqrt{k}}} \int_0^{\frac{M}{\sqrt{k}}} \left(x - \frac{M}{2\sqrt{k}}\right)^2 + \left(y - \frac{M}{2\sqrt{k}}\right)^2 + \left(z - \frac{M}{2\sqrt{k}}\right)^2 dxdydz. \quad (1)$$

From (1), $E[\Theta^2] = k/M^3 \int_0^{M/\sqrt{k}} \int_0^{M/\sqrt{k}} 1/4k[4kx^3/3 - 2\sqrt{k}Mx^2 + 3M^2x - 4\sqrt{k}M(y + z)x + 4k(y^2 + z^2)x]_0^{M/\sqrt{k}} dydz$, $E[\Theta^2] = 1/4M^3 \int_0^{M/\sqrt{k}} \int_0^{M/\sqrt{k}} [4kM^3/3\sqrt[3]{k} - 2M^3/\sqrt{k} + 3M^3/\sqrt{k} - 4M^2(y + z) +$

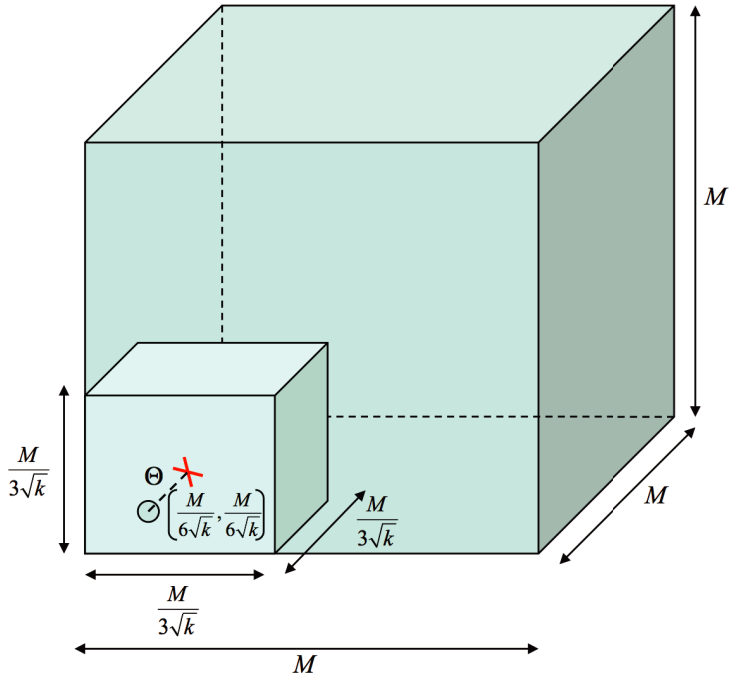


Figure 1. The mean square distance from the sensor to the CH, when the volume measures $M \times M \times M$ with k the number of clusters in a building with the length M.

$4k(y^2+z^2)M/\sqrt{k}]_0^{M/\sqrt{k}}\, dydz$. This can be solved as,

$$E[\Theta^2] = \frac{1}{4M^3\sqrt{k}}\left[\frac{M^3}{3k}\left(5M^2 - 6M^2 + 4M^2\right)\right].$$

Finally, the mean square distance for k cluster ($k > 1$) is given by

$$E[\Theta^2] = \frac{M^2}{4\sqrt[3]{k}}, \tag{2}$$

where $k = j^3$ and j is an integer. We evaluate the mean distance using (2) with the arbitrary value of k as an approximation. The above model (2) is for a cubic volume to demonstrate a three-dimensional building structure. Although (2) applies to $k = j^3$ under our original assumption of square shaped clusters, we use Equation (2) to evaluate the mean distance between the CH and a node in its cluster for any integer value of k. In this work, we assume a comprehensive energy model [14] that features a total energy consumed by sensor node i in cluster j, $E_N(ij)$ per communication round is given by

$$E_N(ij) = bV_s\left(I_{write}T_{write} + I_{read}T_{read}\right) + bV_sI_{sens}T_{sens} + bE_{elec} + bd_{ij}^nE_a + T_AV_s\left[d_NI_A + (1-d_N)I_S\right],$$

where duty cycle $d_N = (T_{tranON}+T_A+T_{tranOFF})/(T_{tranON}+T_A+T_{tranOFF}+T_S)$ and $T_S \gg T_A$. Distance d_{ij} can be substituted from our estimated distance in (2). The estimated energy dissipation, $E_\alpha(k, M)$, is the energy using cluster k and building length M. Now we can obtain the energy dissipation defined by the following single objective unconstrained optimization problem:

$$\min_{\substack{k\in j^3 \\ M\in l_M}} E_\alpha(k, M),$$

that minimizes the energy consumed by sensor node, which involves building length and the number of clusters.

Table 1. Parameter values used in simulation.

Symbol	Description	Value
V_s	Supply voltage to sensor	2.7 V
n	Path loss exponent: free space fading	2
b	Constant: transmit packet size	2 Kb
E_{elec}	Energy dissipation: electronics	50 nJ/bit
E_a	Energy dissipation: power amplifier	100 pJ/bit/m^2
T_{tranON}	Time: sleep → idle	2450 µs
$T_{tranOFF}$	Time: idle → sleep	250 µs
I_A	Current: wakeup mode	8 mA
I_S	Current: sleeping mode	1 µA
T_S	Current: sensor node sleeping time	299 ms
T_A	Current: sensor node wakeup time	1 ms
T_{tr}	Time between consecutive packet	180 s
T_{sens}	Time duration: sensor node sensing	0.5 mA
I_{sens}	Total current: sensing activity	25 mA
I_{write}	Total time: flash writing 1 byte data	18.4 mA
I_{read}	Total time: flash reading 1 byte data	6.2 mA
T_{write}	Time duration: flash writing	12.9 ms
T_{read}	Time duration: flash reading	565 µs
k	number of clusters	0–6

4. SIMULATION AND EXPERIMENTAL DATA SETUP

The energy consumed by a sensor node can be associated with several main basic energy consumption sources: data processing energy by a microprocessor, radio transmission and receiving energy, transient energy, sensor sensing, sensor logging and actuation. The parameter values are listed in Table 1. The total number of sensors considered is $N_s = \sum_{j=1}^{k}(n_j + 1)$. Sensors transmit information to their respective CH. The CH will then forward the packet through a unique route of CHs to the sink node. All transmissions are from the leaves through the intermediate nodes, towards the root (which is the sink node). Let d_j be the distance between CH_j and the next CH (or the sink node) that it transmits to, and d_{ij} be the distance between node i in cluster j and its cluster head. Supply voltage V_s is 2.7 V. It is assumed that each node transmit data once every $T_{tr} = 3$ minutes. The channel bandwidth was set to 1 Mb/s as in [16], and each single packet size is $b = 2$ Kb, which maintains the average data rate requirement per node (< 12 bps). All simulations and analysis were done using MATLAB R2012b on an Intel Core i7 CPU and the experimental datasets of our previous experiments of the link quality distribution in a single floor [17, 18] as well as a multi-storey building [19] of an indoor building environment.

4.1. Statistical Analysis

Probability distribution of the experimental data from single storey as well as multi-storey buildings environment is observed, in order to test for the normality of the distribution. We then computed the mean and standard deviation of the datasets. The geometric mean (GM) is more relevant than the arithmetic mean for explaining the relative progress of the data success rate, hence, the GM of each dataset to estimate of the population can be computed using the below formula. The GM of the data success rate of a data set $x_i = x_1, x_2, \ldots, x_n$, GM_x is given by $\mathrm{GM}_x = [\prod_{i=1}^{n} x_i]^{\frac{1}{n}}$. Using geometric

mean, GM_x, geometric standard deviation, GSD_x is given by $\mathrm{GSD}_x = \sqrt{(\sum_{i=1}^{n}(\ln \frac{x_i}{GM_x})^2)/n}$. The interquartile range (IQR) is a vigorous estimate of the spread of the data, as changes in the upper and lower 25% of the data do not affect it. As an estimate, the IQR is more representative than the standard deviation of the spread of the data, if there are outliers in the data. When the data is from the normal distribution, the IQR is less efficient than the standard deviation as an estimate of the spread. However, we found our data is not normal distribution. Therefore, we analyzed the interquartile range of the datasets of data success rate to observe how data spreads over the 25th and 75th percentiles. The IQR estimate is calculated by $\Theta_{\mathrm{IQR}} = 0.75 \times \mathrm{IQR}$ of the given dataset. Then the efficiency (η) of using Monte Carlo simulation is computed by $\eta = (\frac{||\sigma - 1||}{||\Theta_{\mathrm{IQR}} - 1||})^2$, where the standard deviation of the data is σ.

We then compare the mean data success rate to all other values in different sensors to CH distances. P-value for each comparison is determined using the Wilcoxon Rank Sum test. The null hypothesis in this analysis is that the medians values of the two samples are identical. The alternative hypothesis is that the medians values of the two samples are statistically different. If we consider that the median of the data success rate values of a sensor is β_1 and another value β_2, then H_0: $\beta_1 - \beta_2 = 0$ and H_1: $\beta_1 - \beta_1 \neq 0$. The normal probability values are calculated from the following formula. For each data value $i = 1, 2, \ldots, n$, get x_i such that:

$$P(X < x_i) = \begin{cases} 1 - 0.5^{1/n} & \text{for } i = 1 \\ 0.5^{1/n} & \text{for } i = n \\ \dfrac{i - 0.3175}{n + 0.365} & \text{otherwise.} \end{cases}$$

5. RESULTS AND DISCUSSION

Table 2 was obtained from the above estimation model. We have obtained these results to investigate the optimal distance to place sensors in a building environment. Figure 2 shows the estimated distance from the sensor to the CH for different building sizes and the number of clusters. From this figure, we can also observe that the estimated distance decreases rapidly, with the increasing number of clusters in the same building area. This is due to the decrease in the communication distance. Hence, by optimizing the distance from the sensor to the cluster head, the overall energy consumption can be reduced. For example, if we have a building with 15 m length and we decide to have 3 clusters then the estimated distance from the sensor to the CH will be 3.29 m $\approx$ 3 m. Table 2 shows how the estimated energy dissipation from the sensor to the CH varies with the number of clusters and the building size. Our results show that the clustering is important for single storey and multi-storey building sensor networks; however, when it reaches a certain building size it is unimportant, as can be seen from Table 2.

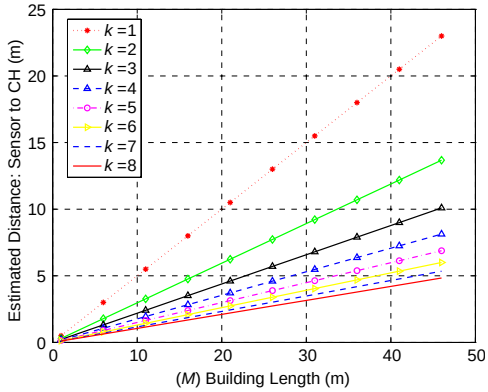


Figure 2. The mean square distance from the sensor to the CH versus building length M with different number of k clusters. This shows the difference between the building length and the number of clusters does have significant effect to the estimation of the distance between from the sensor to the CH.

Table 3 shows the possible building size for different clusters and data success rates from the experimental datasets of the link quality distribution in a single storey building sensor network. As observed from Table 3, the poor link quality in-between regions may be due to the many obstacles that comprises the radio path, for example: concrete element, plasterboard partitions, brick walls, office furniture and other items that either absorbs or reflects these radio waves leading to the signal loss or multi-path effects [17]. This observation can be seen from Table 3 such as the different data success rates for similar distances. Another reason could be that the packets drop during its transmission time.

Besides, Table 4 shows the possible building size for different clusters and data success rates from the experimental datasets of the link quality distribution in a multi-storey building sensor network. The existence of reinforced concrete slabs at each storey and the facade which obstructs the radio signal introduces an additional absorption term to the path loss into the transitional region, in a multi-storey building [19]. These observations can be seen from Table 4, such as different data success rates for similar distances. The experimental data distribution of buildings is plotted in Figure 3 for the

Table 2. Estimated energy dissipation.

Building Length (m)	Estimated Energy Dissipation (mJ) for Different Clusters							
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$
1	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2
6	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2
11	1368.4	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2
16	1369.0	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2	1368.2
21	1370.6	1368.5	1368.3	1368.2	1368.2	1368.2	1368.2	1368.2
26	1373.9	1368.9	1368.4	1368.3	1368.3	1368.2	1368.2	1368.2
31	1379.8	1369.7	1368.6	1368.4	1368.3	1368.3	1368.2	1368.2
36	1389.2	1370.8	1369.0	1368.5	1368.4	1368.3	1368.3	1368.3
41	1403.5	1372.6	1369.5	1368.8	1368.5	1368.4	1368.3	1368.3
46	1424.2	1375.2	1370.3	1369.1	1368.7	1368.5	1368.4	1368.3

Table 3. Single-storey building sensor network: possible building size for different clusters and data success rate.

Distance Sensor to CH (m)	Possible Building Length for Different Clusters (m)								Data Success Rate (%)
	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	
1.8	3.6	6.05	8.21	10.18	12.04	13.80	15.49	17.12	100.00
3.0	6.0	10.09	13.67	16.97	20.06	23.00	25.82	28.54	100.00
10.8	21.6	36.33	49.24	61.09	72.22	82.81	92.95	102.75	97.78
12.2	24.4	41.04	55.62	69.01	81.58	93.54	105.00	116.06	99.94
13.4	26.8	45.07	61.09	75.80	89.61	102.74	115.33	127.48	91.20
17.4	34.8	58.53	79.32	98.43	116.36	133.41	149.76	165.54	63.06
18.4	36.8	61.89	83.88	104.08	123.05	141.08	158.37	175.05	99.91
21.2	42.4	71.31	96.65	119.92	141.77	162.54	182.47	201.69	99.96
21.2	42.4	71.31	96.65	119.92	141.77	162.55	182.47	201.68	99.94
26.4	52.8	88.79	120.36	149.34	176.54	202.42	227.22	251.16	81.64
26.4	52.8	88.79	120.36	149.34	176.54	202.42	227.22	251.16	99.74
30.4	60.8	102.25	138.59	171.97	203.29	233.08	261.65	289.21	100.00
36.0	72.0	121.09	164.12	203.65	240.74	276.02	309.85	342.49	97.22
41.0	82.0	137.91	186.92	231.93	274.18	314.36	352.89	390.06	1.48
41.2	82.4	138.57	187.83	233.06	275.52	315.89	354.61	391.96	37.13

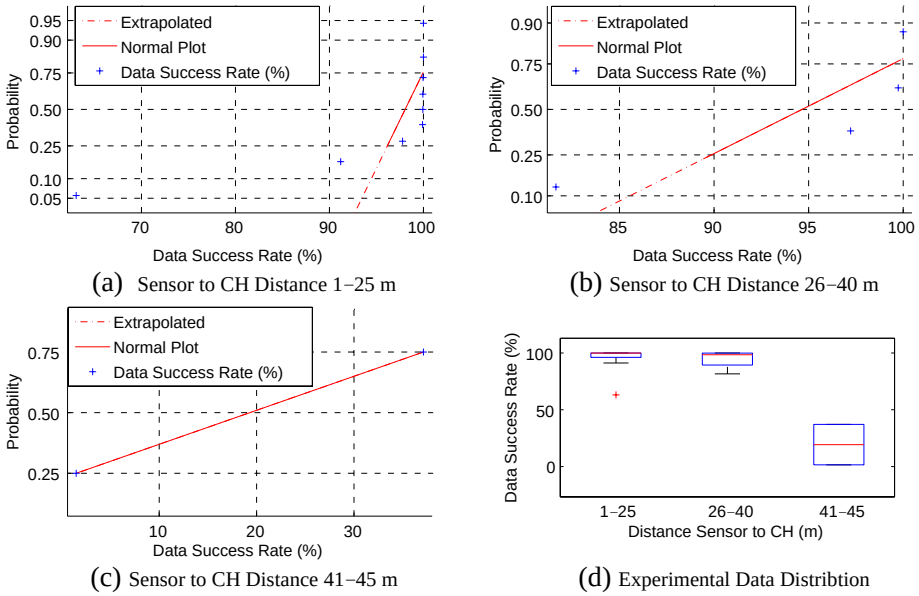


Figure 3. Analysis of experimental data in a single storey building: Normal probability values. (a) Distance 1–25 m. (b) Distance 26–40 m. (c) Distance 41–45 m. These values are computed from the formula explained in the Section 4.1. (d) Data success rate for different distance between the sensor to CH.

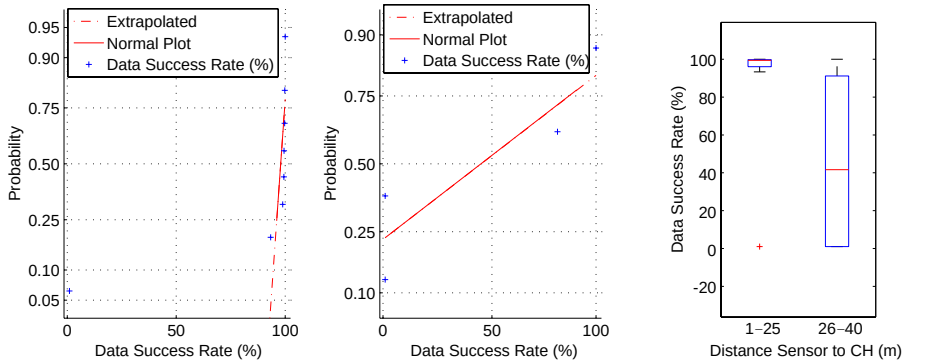
single storey building and Figure 4 for the multi-storey building. We find that our data is not normal distribution as indicated in Figures 3(a)–3(c) and 4(a), 4(b). Table 5 shows the descriptive statistics of the experimental datasets of single storey and multi-storey buildings. The Wilcoxon Rank Sum test analyses suggest that there is no statistically significant difference ($p > 0.05$) of the data success rate for the given distances in indoor building environment (single storey as well as multi-storey buildings). Our results demonstrate that we can save sensor battery energy significantly, by optimizing the distance from the sensor to the cluster head while obtaining the high data success rates. Hence, sensor network designers can use these values to optimize network lifetime.

Table 4. Multi-storey building sensor network with external hub: possible building size for different clusters and data success rate.

Distance	Possible Building Length for Different Clusters (m)								Data Success
Sensor to CH (m)	$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=6$	$k=7$	$k=8$	Rate (%)
11.2	22.40	37.67	51.06	63.35	74.89	85.87	96.39	106.55	99.725
11.7	23.40	39.35	53.34	66.18	78.24	89.71	100.70	111.31	99.369
11.7	23.40	39.35	53.34	66.18	78.24	89.71	100.70	111.30	99.454
13.0	26.00	43.73	59.26	73.54	86.94	99.67	111.89	123.67	99.791
18.6	37.20	62.56	84.79	105.22	124.38	142.61	160.09	176.95	100.00
18.9	37.80	63.57	86.16	106.91	126.39	144.91	162.67	179.81	98.847
18.9	37.80	63.57	86.16	106.91	126.39	144.91	162.67	179.81	93.318
19.7	39.40	66.26	89.81	111.44	131.74	151.04	169.56	187.42	0.000
26.0	52.00	87.45	118.53	147.08	173.87	199.35	223.78	247.35	100.00
26.2	52.40	88.12	119.44	148.21	175.21	200.88	225.50	249.26	0.000
26.2	52.40	88.12	119.44	148.21	175.21	200.88	225.50	249.26	82.303
26.8	53.60	90.14	122.18	151.60	179.22	205.48	230.67	254.97	0.000

Table 5. Values of data success rate (%) in single and multi-storey building (experimental data).

Description	**Single Storey Building**			**Multi-storey Building**	
Distance — Sensor to CH (m)	1–25	26–40	41–45	1–25	26–40
Sample Size	9	4	2	8	4
Mean	94.64	94.65	19.30	86.43	46.07
Standard Deviation (SD)	12.18	8.76	25.21	34.59	52.55
Gemetric Mean	93.77	94.32	7.41	55.55	9.52
Gemetric SD	1.15	1.08	5.00	4.56	9.53
Median	99.94	98.48	19.31	99.41	41.65
(Θ_{IQR}) IQR Estimate of Spread	2.84	7.73	26.43	2.72	66.82
(η) Efficiency — Monte Carlo Simulation (%)	36.86	1.32	0.90	387.39	0.61
p-value (using Wilcoxon Rank Sum test)	0.60	0.80	1.00	0.44	1.00



(a) Sensor to CH Distance 1–25 m (b) Sensor to CH Distance 26–40 m (c) Experimental Data Distribtion

Figure 4. Analysis of experimental data in a multi storey building: normal probability values. (a) Distance 1–25 m. (b) Distance 26–40 m. These values are computed from the formula explained in the Section 4.1. (c) Data success rate for different distance between the sensor to CH.

6. CONCLUSION

The new realistic model to estimate the distance from a sensor to the cluster head of sensor fields suitable for monitoring temperature, light intensity and CO_2 levels in a single storey or multi-storey building is developed. We use our model to evaluate the average distance from a sensor to the cluster head (CH) for the building monitoring. Therefore, minimizing energy dissipation in a battery of the sensor node with limited battery power is a more vital consideration for sensor network lifetime. Our results show that the clustering is important for single storey and multi-storey building sensor networks; however, when it reaches a certain building size it is unimportant. Using experimental data of single storey as well as multi-storey buildings, our results also demonstrate that we can save sensor battery energy significantly, by optimizing the distance from the sensor to the cluster head, while acquiring the high data success rates. Based on this work, designers can optimize energy efficiency, which is very crucial in sensor networks.

REFERENCES

1. Shu, F., M. N. Halgamuge, and W. Chen, "Building automation systems using wireless sensor networks: Radio characteristics and energy efficient communication protocols," *EJSE Special Issue: Sensor Network on Building Monitoring: From Theory to Real Application*, 66–73, 2009.

2. Boulis, A., S. Ganeriwal, and M. B. Srivastava, "Aggregation in sensor networks: An energy-accuracy trade-off," *Proc. Int. Sensor Network Protocols and Applications*, 128–138, 2003.
3. Cayirci, E., "Data aggregation and dilution by modulus addressing in wireless sensor networks," *IEEE Commun. Lett.*, Vol. 7, No. 8, 355–357, Aug. 2003.
4. Sankarasubramaniam, Y., I. F. Akyildiz, and S. W. McLaughlin, "Energy efficiency based packet size optimization in wireless sensor networks," *Proc. IEEE Int. Sensor Network Protocols and Applications Conf.*, 1–8, 2003.
5. Halgamuge, M. N., S. M. Guru, and A. Jennings, "Energy efficient cluster formation in wireless sensor networks," *Proc. IEEE Int. Telecommunications Conf., ICT'03*, Vol. 2, 1571–1576, Tahity, French Polynesia, Feb.–Mar. 2003.
6. Halgamuge, M. N., S. M. Guru, and A. Jennings, "Centralised strategies for cluster formation in sensor networks," *Classification and Clustering for Knowledge Discovery*, 315–334, Springer-Verlag, Aug. 2005, ISBN: 3-540-26073-0.
7. Zou, Y. and K. Chakrabarty, "Target localization based on energy considerations in distributed sensor networks," *Proc. IEEE Int. Sensor Network Protocols and Applications Conf.*, 51–58, May 2003.
8. Halgamuge, M. N., "Efficient battery management for sensor lifetime," *Proc. IEEE AINAW Conf.*, Vol. 1, 56–61, Niagara Falls, Canada, May 2007.
9. Heinzelman, W. R., A. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Tran. on Wireless Comm.*, Vol. 1, No. 4, 660–670, Oct. 2002.
10. Halgamuge, M. N., K. Ramamohanarao, and M. Zukerman, "High powered cluster heads for extending sensor network lifetime," *Proceedings of 6th IEEE International Symposium on Signal Processing and Information Technology (ISSPIT06)*, 64–69, Vancouver, Canada, Aug. 2006.
11. Intanagonwiwat, C., R. Govindan, and D. Estrin, "Directed diffusion: A scalable and robust communication paradigm for sensor networks," Tech. Rep. 00-732, University of Southern California, Los Angeles, 2000.
12. Halgamuge, M. N., *Resource Allocation in Wireless Networks: Cellular and Sensor Networks*, 268, Lambert Academic Publishing, Germany, 2009, ISBN: 978-3-8383-2117-2.
13. Halgamuge, M. N., "Performance evaluation and enhancement of mobile and sensor networks," Ph.D. Dissertation, Department of Electrical and Electronic Engineering, The University of Melbourne, Melbourne, Australia, 2007.
14. Halgamuge, M. N., "Design factors for sustainable sensor networks," *Proc. 3rd Int. Conf. on Information and Automation for Sustainability*, 106–110, Melbourne, Australia, Dec. 2007.
15. Halgamuge, M. N., M. Zukerman, K. Ramamohanarao, and H. L. Vu, "An estimation of sensor energy consumption," *Progress In Electromagnetics Research B*, Vol. 12, 259–295, 2009.
16. Heinzelman, W. B., A. P. Chandrakasan, and H. Balakrishnan, "An application-specific protocol architecture for wireless microsensor networks," *IEEE Trans. Wireless Commun.*, Vol. 1, No. 4, 660–670, Oct. 2002.
17. Halgamuge, M. N., T. K. Chan, and P. Mendis, "Experimental study of link quality distribution in sensor network deployment for building environment," *EJSE Special Issue: Sensor Network on Building Monitoring: From Theory to Real Application*, 28–34, 2009.
18. Halgamuge, M. N., T. K. Chan, and P. Mendis, "Experiences of deploying an indoor building sensor network," *Third International Conference on Sensor Technologies and Applications, SENSORCOMM'09*, 378–381, Athens, Greece, Jun. 2009.
19. Halgamuge, M. N., T. K. Chan, and P. Mendis, "Improving multi-story building sensor network with an external hub," *World Academy of Science, Engineering and Technology*, Vol. 52, 420–423, Apr. 2009.