Modeling of WSN Energy Consumption
Supplied by iPV Microsystem

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Abstract Current researches on wireless sensor networks (WSN) are focusing on reducing the total amount of energy consumption and extending the network lifetime. WSN have many application fields like industry, health care, commercial and residential applications. The main goal of this paper is to evaluate, using MATLAB/Simulink simulations, the average amount of energy consumed in a WSN based on a clustering topology; to predict the optimal number of clusters in order to optimize the energy and also to study the cloud integration effects on lifetime and energy time dependency. The clustering topology is based on defining K clusters with N/k nodes, each node transmits data to the cluster head which will collect data from all of its own nodes, compute it and send it to the base station (BS). In our simulation, we have focused on many principal metrics in WSN such as optimal number of clusters, duty cycle, lifetime and distance to BS. Finally we have studied the effect of integrating cloud into classic WSN, the effect in terms of energy consumption and sensor node lifetime.

Keywords WSN, Harvesting, MATLAB, Cloud, Duty Cycle, Lifetime, Cluster, Node

1. Introduction

Wireless sensor networks (WSN) are more and more present in residential, commercial and industrial applications. In fact, they are found in intelligent buildings, in medicine and healthcare, agricultural control, logistics and many other fields.

Moreover, the huge interest given recently to Internet of Things (IoT) is boosting the research on WSN. The major problem in WSN technology is energy supply. Indeed, batteries have a seriously limited capacity, need to be periodically replaced and are harmful to environment. Consequently, the current research on wireless sensor network is focusing on reducing the total amount of energy consumption and extending the network lifetime [1]. Accurate estimation of sensor network lifetime requires, of course, an accurate energy consumption model.

In this work, nodes are distributed according to a cluster-like distribution which is a commonly used topology. A node is randomly chosen to be a cluster head but it has to have the needed energy available.

In this paper, we review the models used to evaluate the energy consumption and lifetime in the case of a cluster-based WSN. We put a particular emphasis on conditions where energy consumption reduction and lifetime improvement are the most effective.

In the first section, we present and put in coherence two energy consumption models: the first one (M. N. Halgamuge and al. ‘s model [2]) gives an expanded equation describing all the commonly used sensor functions, while the second model (Heinzelman et al. model [3]) focusses only on the most energy-consuming part.

In the second section, we report the simulation results where the crucial WSN parameters are studied, like the distance to the base station, Duty cycle and number of clusters. This helped to study both network energy consumption and network lifetime.

Another way to analyze and explore energy and lifetime improvements is to integrate cloud. When integrating cloud into WSN, several shortfalls, such as storage capacity of collected data with data processing tasks on sensor nodes, would become much easier [4] saving, by the way, the related energies. Such approach is developed in the third section.

2. Sensor Energy Consumption versus Network Parameters

2.1. Network Model

In this work, we assume a network with N=100 immobile homogeneous nodes randomly distributed on
Consider k the number of clusters in the network, in each cluster there are \( \binom{N}{K} \) nodes and one Cluster Head (CH). CH’s are special wireless nodes, with sufficient power available, which can send data to base station (BS) directly or via other CH’s called CH-parents. The simple node senses physical signal and converts it to electrical signal. Signal conditioning and analog to digital conversion are also within node processing tasks [2]. Then, the node transmits the signals only to its related CH and not to BS. Each transmitted data message is fixed to b= 4000 bits long [5]. Figure 2 shows a network with a cluster tree topology: Each CH receives data from its own nodes or from other CH’s called CH-children and transmits it to its CH-parent. A CH-parent can have many CH-children.

2.2. Communication Energy Dissipation Model (EDM)

Figure 2 presents a communication package mainly composed of the transmitter and the receiver circuits. It represents what is called the first order Radio Model. b is the number of bits per transmitted packet and d is distance between the sender and the receiver. Energy consumed to receive a b bit packet is expressed as follows:

\[
E_{Rx}(b) = b \cdot E_{elec}
\]  

(1)

Energy transmitted to transmit a b bit data packet, the radio expends:

\[
E_{Tx}(b, d) = b \cdot E_{elec} + E_{amp} (b, d)
\]  

(2)

Where:

\( E_{elec} \) is the energy dissipated per bit to run the transmitter or the receiver electrical circuit and \( E_{amp} (b, d) \) is the amplifier energy consumption. Moreover we have to count the power loss factor for free space fading \( (d^2) \) or multipath fading \( (d^4) \) depending on the distance, as follows:

\[
E_{Tx}(b, d) = \begin{cases} 
(E_{elec} \cdot b) + (e_{fs} \cdot b \cdot d^2), & \text{if } d < d_0 \\
(E_{elec} \cdot b) + (e_{mp} \cdot b \cdot d^4), & \text{if } d > d_0 
\end{cases}
\]  

(3)

Where:

\[
d_0 = \sqrt{\frac{e_{fs}}{e_{mp}}}
\]  

(4)

For the simulation described in this paper, we used typical radio parameter settings: \( E_{elec} = 50\text{nJ/bit} \), \( e_{fs} = 10\text{pJ/bit/m}^2 \) and \( e_{mp} = 0.0013\text{pJ/bit/m} \) and energy for data aggregation \( E_{DA} = 5\text{nJ/bit/signal} \) [3]. Some models like M. N. Halgamuge et al. [7] consider the total energy consumed by the sensor as the sum of different specific energies such as sensing, logging, micro-controller processing, radio transmitting and receiving, actuating and transient energy. The global network energy consumption equation is, then, given by:
\[ E_{tot} = k \cdot E_{\text{cluster}} = b \left( N \cdot E_{\text{elec}} + N \cdot E_{\text{proCH}} + k \cdot e_{mp} \cdot d_{toBS}^4 \right) + k \cdot E_{\text{sensCH}} + k \cdot E_{\text{tranCH}} + k \cdot E_{\text{loggCH}} + N \cdot E_{\text{elec}} + N \cdot e_{fs} \cdot \frac{M^2}{2 \pi K} + N \cdot E_{\text{tranN}} + N \cdot E_{\text{sensN}} + N \cdot E_{\text{loggN}} \] (5)

Where:
- \( d_{toBS} \) is the distance from CH to the BS, and
- \( E_{\text{proCH}}, E_{\text{sensCH}}, E_{\text{tranCH}}, E_{\text{loggCH}} \) are respectively processing, sensing, transient, logging energy in a CH and
- \( E_{\text{tranN}}, E_{\text{sensN}}, E_{\text{loggN}} \) are respectively transient, sensing and logging energy in a node.

Others, like Heinzelman and al. focus only on communication and computation components \([8][9]\) because they are the two prominent energy consumption tasks (about two thirds). We have adopted such a simplified expression to compute the total energy, considering the energy for data aggregation \( E_{DA} \) as a constant.

Energy consumed by the network is the energy consumed in one cluster \( E_{\text{cluster}} \) multiplied by \( K \) total number of clusters.

\[ E_{\text{cluster}} = E_{CH} + \frac{N}{K} - 1 \] \( E_{\text{CH}} = b E_{\text{elec}} \left( \frac{N}{K} - 1 \right) + b E_{\text{DA}} \cdot \frac{N}{K} + b E_{\text{elec}} + b e_{mp} \cdot d_{toBS}^4 \]

\[ E_{\text{non-CH}} = b E_{\text{elec}} + b e_{fs} \cdot d_{toCH}^2 \]

If sensors are placed uniformly over a circle area then the mean square distance from a sensor to its CH is given by \([11]\):

\[ d_{toCH}^2 = \frac{M^2}{2 \pi K} \] (6)

Total energy per frame is:

\[ E_{tot} = k \cdot E_{\text{cluster}} = b \left( N \cdot E_{\text{elec}} + N \cdot E_{DA} + k \cdot e_{mp} \cdot d_{toBS}^4 + N \cdot E_{\text{elec}} + N \cdot e_{fs} \cdot \frac{M^2}{2 \pi K} \right) \] (7)

Several simulation environments for WSN do exist, like GloMoSim/QualNet, OPNET, Modeler Wireless Suite, OMNeT++ and NS-2. The environment in which we carried out our simulation was Simulink MATLAB. Simulink provides a graphical user interface (GUI) for building models as block diagrams, using click-and-drag mouse operations \([12]\) and it provides an interactive graphical environment and a customizable set of block libraries which facilitate the designing, simulation, implementation, and testing of a variety of systems\([13]\).

Figure 3. MATLAB/Simulink Simulation Model
Table 1 contains Parameter values used in our simulated energy model:

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$E_{elec}$</td>
<td>Energy dissipated in electronics</td>
<td>50nJ/bit</td>
</tr>
<tr>
<td>N</td>
<td>Number of Nodes</td>
<td>100</td>
</tr>
<tr>
<td>b</td>
<td>Data packet size</td>
<td>4000 bits</td>
</tr>
<tr>
<td>$\epsilon_{mp}$</td>
<td>Multipath fading energy</td>
<td>0.0013pj/bit/m</td>
</tr>
<tr>
<td>$d_0$</td>
<td>Threshold distance</td>
<td></td>
</tr>
<tr>
<td>EDA</td>
<td>Energy for data aggregation</td>
<td>5nJ/bit/signal</td>
</tr>
<tr>
<td>$\epsilon_{fs}$</td>
<td>Free space fading energy</td>
<td>10pj/bit/m$^2$</td>
</tr>
<tr>
<td>$M$</td>
<td>Area surface</td>
<td>100*100M</td>
</tr>
<tr>
<td>$T_{TON}$</td>
<td>Time duration to transit from sleep to idle</td>
<td>2450$\mu$s [14]</td>
</tr>
<tr>
<td>$T_{TOFF}$</td>
<td>Time duration to transit from idle to sleep</td>
<td>250$\mu$s[14]</td>
</tr>
<tr>
<td>$T_A$</td>
<td>Active time</td>
<td>1ms[14]</td>
</tr>
<tr>
<td>$T_S$</td>
<td>Sleeping time</td>
<td>299ms[14]</td>
</tr>
<tr>
<td>$I_A$</td>
<td>Current: wakeup mode</td>
<td>8mA</td>
</tr>
<tr>
<td>$I_S$</td>
<td>Current: sleeping mode</td>
<td>1 $\mu$A</td>
</tr>
</tbody>
</table>

2.3. LEACH Protocol Operations

The time-line LEACH operations are composed principally of set-up phase and steady state phase. In the set-up phase, nodes organize themselves into clusters (all nodes Decide of Being CH, All CH send their position and approval request to the sink node, Scheduling all CH, all nodes are listening to their CH, ALL nodes Decide to get associated to CH depending on the maximum power received [15]). In the steady-state phase, nodes transmit data to their own CH in their assigned time slots. In each frame, there are N numbers of data slots. Node i transmit its data during its time slot in each frame.

Finally, All CH transmit the aggregated data to the sink.

\[ E_{CH per round} = N_{frames per round} \times E_{CH per frame} \] (8)

The simulations’ results are shown in next session.

The percentage of energy consumption per function were estimated in [2]; communication has the biggest part by 51% from total WSN energy consumption, processing 12%, transient 10%, logging 14%, sensing 6%, actuation 8% and initial energy 1%. We can then represent a histogram of energy consumption sources considers by various models.
3. Simulation Results

3.1 Optimal Clusters Number

In order to minimize the energy consumption inside the WSN, sensor nodes must be distributed according to an optimal number of clusters, \( k_{opt} \). The latter is obtained by differentiating the total consumed WSN energy with respect to the clusters number (\( k \)) and setting it to zero. Then, we obtain:

\[
 k_{opt} = \frac{M\sqrt{\pi f_s}}{d_{toBS} \sqrt{2\pi} \epsilon_{mp}}
\]  

(9)

Next figure (4) shows the dependence of the \( k_{opt} \) versus the distance to the base station (\( d_{toBS} \)) or the sink node.

![Figure 6. Optimal number of Clusters vs distance from CH to the sink node (BS) -Analytical results for \( N=100 \) nodes, \( M=100 \), \( \text{Efs}=10\text{pJ/bit/m}^2 \) and \( \text{Emp}=0.0013\text{pJ/bit/m}^4 \)]

We can notice that the optimal number of clusters depends strongly on the distance to the base station and reaches the minimum, one cluster, around 190m. We conclude that this topology (Tree cluster based WSN) is well adapted for small and medium surfaces deployment (residential and industrial units). Moreover, one of the crucial issues in cluster based networks is to determine the optimal number of clusters minimizing the total WSN energy consumption.

![Figure 7. Average Energy Consumption per round (J) in LEACH when the number of Clusters (k) is varied between 1 and 11]

When varying the number of clusters between 1 and 11, figure (5) shows that optimal number of clusters, \( k_{opt} \), is
between 2 and 4.

### 3.2. Network Lifetime vs. Duty Cycle

Depending on the sensor network topology and the corresponding applications, lifetime is defined as either the time until the first (or last) node dies or the time until a given percentage of nodes dies [16, 17]. Duty cycling is a technique where a node is periodically placed into the sleep mode which is an effective method of reducing energy dissipation in wireless sensor networks [18]. The duty cycle expresses the ratio between the time when the node is on and the sum of the times when the node is on and asleep so a DC of 100% is a continuous working node. So it can be expressed by:

\[
C_N = \frac{T_{ON} + T_{OFF} + T_A}{T_{ON} + T_{OFF} + T_A + T_S}
\]  

(10)

Where \(T_{ON}, T_{OFF}, T_A\) and \(T_S\) are time durations to respectively transit from sleep to idle mode, transmit from idle to sleep, active time and sleeping time.

The lifetime of the node depends on the capacity of the battery:

\[
\text{Node lifetime} = \frac{\text{initial battery capacity}}{\text{avg current} \times 365 \times 24} \text{ [years]}
\]  

(11)

The average current for a sensor node is given by:

\[
I_N = C_N I_A + (1 - C_N) I_S
\]  

(12)

Where \(I_A\) and \(I_S\) are currents for active and sleeping mode.

Next we will present the variation of lifetime of one node as function of the duty cycle which is one of the basic and most commonly used power management techniques.

![Figure 8. Sensor node lifetime vs. Duty Cycle(%)](image)

The parameter values are taken from Table 1 and used in equation (10). As the figure (6) shows, when the duty cycle increases the lifetime of the node decreases; so we can conclude that lifetime of a sensor node is inversely proportional to the duty cycle. Low duty cycle is more appropriate for long lasting WSNs.

### 3.3. Average Energy Consumption vs Distance from CH to BS

In WSN, energy has to be managed very carefully in order to increase the network performance. In this section, the average energy consumed per round vs the distance from CH to BS (dtoBS) is evaluated. As expected, when (dtoBS) increases, the average energy consumed increases and thus, the WSN lifetime decreases.
4. Cloud Integration Effects on Lifetime and Energy Time Dependency

Sensor Networks have several limitations in terms of energy. Many techniques are being developed to save energy in WSN. The most commonly used are data aggregation and processing, Mobile sink for data collection, smart activity scheduling, Topology reorganization, data compression, routing protocol [19-22]. Cloud Computing is one of the promising technologies that could help developing lower energy consumption and longer lifetime in sensor networks. Indeed, when integrating cloud into WSN working process, several shortfalls - like data storage capacity and data processing - become more efficient and easier [4].

4.1. Cumulative Sensor Node Energy Consumption

“Sudip Misra et al.” have estimated that a sensor cloud achieves 36.68% decrease in energy consumption, as compared with the case of a classic WSN [23]. In order to better study the behavior of the reduction rate in network energy, based on the reference [23], we have digitized a figure of “Comparative analysis for energy consumption” using the software Get Data Graph digitizer. Then we have proceeded to a fitting of both curves “Total expense in sensor cloud” and “Total expense in WSN”.

Figure 9. Average Energy Consumption per round (J) vs distance to the base station

Figure 10. Cumulative energy consumption vs. time (months): (a) curve of reference for classic WSN, (b) curve of reference for cloud WSN, (c) curves obtained by fitting for classic WSN, (d) curves obtained by fitting for cloud WSN
When fitting, we can notice that next the equation ties in to the curve of cloud computing WSN energy consumption:

\[ F(x) = \frac{5}{6} \log \left( \frac{1}{1 - \frac{x}{100}} \right) \quad (13) \]

And this one ties in to the curve of classic WSN energy consumption:

\[ f(x) = \frac{x}{4} \log \left( \frac{1}{1 - \frac{x}{100}} \right) \quad (14) \]

The gap of energy is expressed as follows:

\[ G_E = \left| \frac{E_{\text{w}}_{\text{classic}} - E_{\text{w}}_{\text{cloud}}}{E_{\text{w}}_{\text{classic}}} \right| \times 100\% \quad (15) \]

Where \( E_{\text{w}}_{\text{classic}} \) and \( E_{\text{w}}_{\text{cloud}} \) are respectively cumulative energy consumption in a classic WSN and in a cloud WSN. We can then conclude that the gap of energy, estimated from the fitting equation, is constant in time and equal to 42.8% compared to 36.68% on Sudip Misra work.

4.2. Sensor Node Lifetime Reduction Rate

As the energy consumed in the sensor network decreases by integrating cloud, this will affect also the sensor node’s lifetime. Some researchers estimated that sensor cloud increases the lifetime by 3.25% [23]. In order to better study this increase in lifetime, we have digitized figure 7 titled “Comparative analysis of sensor node lifetime” from the reference [23]. Figure 10 illustrates a comparative analysis of sensor Node lifetime reduction rate.

![Figure 11. Lifetime reduction Rate vs time (months): (a) curve of reference for classic WSN, (b) curve of reference for cloud WSN, (c) curves obtained by fitting for classic WSN, (d) curves obtained by fitting for cloud WSN](image)

Thanks to logarithmic fittings, the sensor node’s lifetime on a classic network can be expressed as follows:

\[ z(x) = 5.4 + \log \left( 1 - \frac{x}{70} \right) \quad (16) \]

And a sensor node’s lifetime in a cloud computing network can be expressed as follows:

\[ Z(x) = 5.4 + \log \left( 1 - \frac{x}{113} \right) \quad (17) \]

In Figure 10, we depict the reduction rate between classic and cloud WSN sensor node’s operation period (lifetime), where the reduction rate is expressed as follows:

\[ G_L = \left| \frac{L_{\text{w}}_{\text{classic}} - L_{\text{w}}_{\text{cloud}}}{L_{\text{w}}_{\text{classic}}} \right| \times 100\% \quad (18) \]

In this graph, we can evaluate the gap at any point of time during 60 months.
Based on the logarithmic equation, the average lifetime reduction rate during 60 months is 3% compared to 3.25% on the Sudip Misra Work.

5. Dimensioning of PV Harvester to Supply a Sensor Node

Amorphous silicon (a-Si) PV cells have a relatively high efficiency at low light levels, compared to other types of cell. This makes them particularly suited to indoor use. In most cases, a solar cell panel consists of multiple solar cell elements connected in parallel and/or series, where the current source of the solar cell is dependent on the intensity of the incident light.

Since the light is estimated to be available in an office only for 8 hours, and the sensor operates all day, then the output of a PV cell power should be greater than the power consumed by the node on the active mode multiplied by 24h/8h.

Photovoltaic harvesting is a promising energy source because of the available irradiance both indoors and outdoors [23-24]. We consider that the sensor sleeps when not being active using a current of 2.95 µA and a voltage of 3.18V and requesting and receiving data for 5 secs. This leads to an energy consumption of 17.6 J/day or 4.9mWh/day [25].

Table 2. Energy and power densities from a solar cell

<table>
<thead>
<tr>
<th>Average WSN energy consumption (mWh/day)</th>
<th>Irradiance (mW/cm²)</th>
<th>hours</th>
<th>Average Power generated (mWh/cm²)</th>
<th>Cell surfaces (cm²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.9</td>
<td>0.12</td>
<td>8</td>
<td>0.172</td>
<td>28.3</td>
</tr>
</tbody>
</table>

Amorphous-silicon and dye-sensitized solar cells have been tested extensively as indoor light harvesters due to their wide band gaps that are optimum for absorption of the spectra from compact fluorescent lamp (CFL) and light-emitting diode (LED) bulbs [26]. An additional feature of amorphous silicon (and, indeed, all non-crystalline) PV cells is that their MPP voltage (V_{mpp}) is approximately proportional to their open-circuit voltage (V_{oc}). The amorphous silicon solar cell was judged as the most suitable cell for indoor conditions in terms of efficiency reaching 18% for 0.172 mWh/cm² [27] of averaged energy delivered. The sensor with an energy consumption of 4.9mWh/day could thus be powered with an amorphous silicon solar cell with a surface of 28.3cm².

In [28], the author adopted an a-Si 55mm x40mm Sanyo AM1815/16 module series PV cell and in [29] they used a Schott Solar 1116929 amorphous silicon PV cell placed on an office desk under 200-700 lux and the size of the adopted PV modules is greater than 20cm.

Our presented credit card-sized indoor series connected photovoltaic energy harvester (less than 80 mm × 50 mm) supplies 1mW to the WSN mote when the PV cell is under 700–800 lux indoor light in a typical office building environment. Larger PV cells provide higher charging...
currents but that implies oversized harvesting system.

6. Conclusions

In this paper, we showed that the cluster-based WSN, with 3 clusters and 100 nodes, is suitable for residential and professional uses, spread on near 100 square-meters areas. In such a configuration, the energy-consumption model used is based on the major consuming component related to communication and processing. We also showed that, in the studied case, the integration of Cloud computing in the WSN applications reduces the energy consumption by 42.8% and increases the lifetime by 3%.

Finally we justified that a credit card size PV cell could give a sufficient energy for the sensor node corresponding to the available indoor light.

REFERENCES


[14] Rabia Enam, Mumtazul Imam, Rehan Qureshi “Energy consumption in Random Cluster Head selection Phase of WSN” 


