Lifetime Estimation of Sensor Device with AA NiMH Batteries

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Abstract. Lifetime is the primary issue in wireless sensor networks. Temperature is one of important factors affecting node lifetime since it may increase or decrease lifetime of node. This paper proposes a novel equation for node lifetime estimation which covers the effect on both battery capacity and current draw of node. The effectiveness of the proposed scheme is evaluated by using an experimental testbed with various brands, capacity and aging of commercial batteries. Two lifetime estimation techniques are evaluated and compared to the actual node lifetime. By using the proposed technique, lifetime can be estimated for different starting voltages, brands, capacities, ages of batteries and static load programmes without detailed knowledge of electrical and electrochemical.

Keywords: Wireless Sensor Networks, Energy Consumption, Lifetime, NiMH Battery, Voltage, Temperature

1. Introduction

Node lifetime is one of major concerns for Wireless Sensor Networks (WSNs). With accurate lifetime estimation of the sensor nodes, applications or routing protocols are able to make intelligent decisions that can help conserve energy. A WSN node is typically battery powered by AA-size batteries. For example, a pair of AA cells is used for Sensinode N740 NanoSensors using CC2430/2431 SoC [1]. These sensors support battery and temperature monitoring. A common AA rechargeable battery is a nickel-metal hydride cell (NiMH) at 1.2 volts which has capacity ranging from 1100 mAh (milliampere-hour) to 3100 mAh and the self discharge rates are 5-10% or more in first 24 hours and then 0.5-1% per day at room temperature [2]. The starting voltage of fully charged cell in good condition is about 1.4-1.45 volts.

Calculations based on datasheet are usually used to estimate node lifetime for many studies both in simulation and on real hardware. Fixed voltage and fixed temperature are normally assumed (e.g., 3 volts and 25 °C). This means running the static load programmes for multiple times always consume the same energy. However, in reality, they might require different powers which results in the different lifetimes. Moreover, the non-linear behaviour of the batteries should be taken into account. This paper proposes the lifetime estimation by using starting voltage of battery and temperatures. The effect of temperature on battery efficiency and current consumption is covered. The testbed experiment is used to verify the proposed idea with different brands, capacities, ages of NiMH AA-size of batteries and different programmes.

2. Related Work

There are variables used to describe about voltage. Terminal voltage (Vt) is the voltage between the battery terminals with load applied, while open-circuit voltage (VoC) is voltage with no load applied, and Vdd is the positive supply voltage. SoC is the present percentage of maximum capacity (Cmax). Lifetime (Lt) of a node depends on current battery capacity (C0) and consumption needed by that node (I). Lifetime of a node is expressed as [3].
where $C_b$ is $\text{SoC} \cdot C_{\text{max}}$ and $k$ is the peukert constant which can be assumed $k=1$ for low current consumption (less than 0.2 of $C_b$) [4, 5, 6]. To estimate the lifetime of node, it is necessary to estimate both battery capacity and current consumption. Since chemical energy in battery cells is converted into electrical energy through an electrochemical reaction, Nagarajan and Zee [7] proposed the electrochemical models based on the chemical processes that take place in the battery. This model described the battery processes in great details but it is very complex and required highly detailed knowledge of electrochemical which make a difficult setting. Guoliang et al. [8] proposed NiMH battery capacity estimation based on Electromotive Force Method (EMF). From their study, $\text{SoC}$ can be modelled as a linear function, for example, during capacity 80-100% as \((0.8 + (0.2 \cdot (\frac{\text{VoC} - \text{VoC}_{80}}{\text{VoC}_{f} - \text{VoC}_{80}})))\), where $\text{VoC}_{80}$ and $\text{VoC}_{f}$ are the voltages at capacity 80% and 100% and $\text{VoC} \geq \text{VoC}_{80}$. However, the maximum possible battery capacity may decrease due to capacity loss, which is caused by many factors, such as battery ages, number of charge cycles, and charge and discharge behavior on a regular basis. To cover capacity loss, the equation can be expressed as:

$$\text{SoC} = (1-\%\text{loss}) \cdot (0.8 + (0.2 \cdot ([\frac{\text{VoC} - \text{VoC}_{80}}{\text{VoC}_{f} - \text{VoC}_{80}}])))$$  \hspace{1cm} (2)

This model is much easier than the electrochemical models and computationally less expensive. However, it did not cover the current consumption of devices. Furthermore, this method is less accurate as claimed in [9]. To estimate current consumption of node, Liao et al. [10] tried to find the average leakage current consumption, however, detailed knowledge of electrical circuits are required. Jiang et al. [11] develop a hardware-based mechanism for measuring the energy consumption. However, it is a significantly higher cost for energy estimation. Dunkels et al. [12] proposed a formula to calculate the energy consumption ($E$).

$$E/V = I_a t_a + I_l t_l + I_t t_t + I_r t_r + \sum I_c t_c$$  \hspace{1cm} (3)

where $V$ is the supply voltage, $I_a$ and $t_a$ are the current consumption of the MCU (Microprocessor Control Unit) and time when the MCU has been running in active mode, $I_l$ and $t_l$ are the current consumption and time of the MCU in low power or sleep mode, $I_t$ and $t_t$ are the current consumption and the time of the communication device in transmit mode, $I_r$ and $t_r$ are the current consumption and time of the communication device in receive mode, and $I_c$ and $t_c$ are the current consumption and time of other components such as sensors and LEDs. In this model, supply voltage and all current consumption were assumed as fixed values which may not accurate in real-world deployments since they are usually dynamic based on temperatures. Moreover, they did not consider the battery capacity. The impact of battery capacity on lifetime was studied experimentally by Nguyen et al. [13] for different alkaline battery brands but temperature effect was not included in this study. The model proposed by Park et al. [14] covered the remaining capacity and the effect of temperature on battery capacity. However, they did not consider the effect of temperature on the current consumption of devices. Furthermore, their assumption that the batteries begin with full capacity voltage might not be applied in real deployments with NiMH batteries because these batteries had a relatively high self-discharge rate on the first day after full charging.

This paper presents formula for lifetime estimation which covers temperature effect on both battery capacity and current consumption. Moreover, many factors of the different capacity of battery, such as starting voltage due to self-discharging, battery models, brands, aging and different programme loads are also investigated. This model does not require detailed electrical and electrochemical knowledge.

### 3. Lifetime Estimation Model

Normally, higher starting $\text{VoC}$ gives the higher battery power which result in the longer lifetime period. Both battery capacity and current consumption are affected by temperatures. As temperature increases, current draw is increased and, consequently, shorten the lifetime of the device. However for NiMH cells, high temperatures can provide increased capacity of battery over the operating temperature range 0 °C to 30 °C. Therefore, it depends on the ratio between increased battery capacity and current draw, which may result in increased or decreased lifetime. The ratio of capacity at two different average temperatures in Kelvin ($T_1$, $T_2$) can be expressed as [3]:

$$\frac{C_{T_1}}{C_{T_2}} = \left(\frac{T_2}{T_1}\right)^{k-1}$$  \hspace{1cm} (4)

where $C_{T_1}$ is the battery capacity at temperature $T_1$, $C_{T_2}$ is the battery capacity at temperature $T_2$, and $k$ is the temperature coefficient.
\[
\frac{C_b(T_2)}{C_b(T_1)} = \exp^{(A*(T_2-T_1)/(T_2*T_1))} \tag{4}
\]

where \(A\) is a constant ratio between the activation energy and gas of battery. The leakage current draw at two different average temperatures in Kelvin \((T_1, T_2)\) is [10]:
\[
\frac{l(T_{2,Vdd})}{l(T_{1,Vdd})} = (T_2^2/T_1^2) * \exp^{(K*(T_2-T_1)/(T_2*T_1))} \tag{5}
\]

where \(K\) is a constant depended on average \(V_{dd}\) and is assumed that it is the same for running with the same starting voltage and device. From equation (1), (4) and (5), new equation of full capacity voltage \(V_{OC}\) at two different temperatures in Kelvin is derived as:
\[
\ln\left[\frac{(L_t(T_2,V_{OC})*T_2^2)}{(L_t(T_1,V_{OC})*T_1^2)}\right] = \sigma_f *((T_2 - T_1)/(T_2*T_1)) \tag{6}
\]

where \(\sigma_f\) is the difference between \(A\) and \(K\) values for full capacity voltage. This value can be obtained after applying \(L_t(T_1,V_{OC})\), \(L_t(T_2,V_{OC})\), \(T_1\) and \(T_2\) by the experiment measurement values. Time until dead from starting voltage \(V_{OC}\) can be estimated for any average temperature \(T\) which is between \(T_1\) and \(T_2\) as:
\[
L_t(T,V_{OC}) = (L_t(T_{ref},V_{OC})*T_{ref}^2*\exp^{(\sigma_f*(T-T_{ref})/(T*T_{ref}))})/T^2 \tag{7}
\]

where \(T_{ref}\) and \(L_t(T_{ref},V_{OC})\) can be either \((T_1,L_t(T_1,V_{OC}))\) or \((T_2,L_t(T_2,V_{OC}))\). The steps are repeated on another starting voltage \(V_{OC}\) in order to find \(L_t(T, V_{OC})\). If \(V_{OC} \geq V_{OC}\), total lifetime of starting voltage \(V_{OC}\) on average temperature \(T\) can be modelled by:
\[
L_t(T,V_{OC}) = -\tau * \ln(V_{OC}/V_{OC}) + L_t(T,V_{OC}) \tag{8}
\]

where \(\tau\) is the time constant [3] representing capacity affected by self-discharging, and it can be obtained by \(-\Delta t/\ln(V_{OC}/V_{OC})\), where \(\Delta t\) is the different time period between starting at \(V_{OC}\) and \(V_{OC}\) which is \(L_t(T, V_{OC}) - L_t(T, V_{OC})\).

### 4. Lifetime Estimation Verification

To verify the lifetime estimation, a testbed consists of four sensors (N740 sensinode), three of NiMH rechargeable battery brands (Energizer 1300, GP 2100 and maxE 2500), and three of different programmes (P1, P2, P3). One node is a reference node reporting temperature values every minute by using temperature monitoring feature of N740 sensinode. Starting \(V_{OC}\) is measured by a multi-meter. Mapping between nodes, battery brands and programmes is shown in Table 1 and time periods in each mode of each programme are listed in Table 2. Based on Eq. (1), both battery capacity and current consumption estimation are needed. Owing to battery aging, it is assumed that battery capacity loss 30% for GP2100, 10% for maxE2500 and 0% for E1300. Full capacity is based on battery types, for example, 2100 mAh, 2500 mAh and 1300 mAh are for GP2100, maxE2500 and E1300, respectively. From vendor datasheet [4, 5, 6], voltages of 100% and 80% capacity are 2.8 and 2.6V. These values are used for capacity estimation based on equation (2). From CC2430 datasheet [1], current consumption at 25 °C and 3V of \(V_{dd}\) for TX, RX, CPU-ACTIVE, CPU-LOW and SENSING are 26.9, 26.7, 0.19, 10.5 and 1.2 mA, respectively. As equation (3), energy consumption rate can be calculated for P1, P2 and P3 as 75.66, 75.13 and 74.70 mA per minute. From experiments, it is observed that full capacity voltages for GP2100, maxE2500 and E1300 are 2.85, 2.83 and 2.90 V, respectively. After one day, their voltages dropped to around 2.70, 2.75 and 2.80 by self-discharging. These full capacity voltages and values of one day voltage drop are used as \(V_{OC}\) and \(V_{OC}\) to estimate lifetime based on our proposed technique in Eq (8). To find all constant values, each node needs to run several times for these two starting voltages on different temperatures. After finding all constant values, each node runs 10 times with random starting voltages and different temperatures. Our testbed runs on the room temperature range 17.5 and 22 °C. The comparison between estimated lifetimes and measured lifetimes ordering from low to high starting voltage is illustrated in Fig. 1. The results show that all estimated lifetimes based on Eq. (1) have increased based on starting voltages, while the real measured lifetimes sometimes vary based on temperatures. The temperature effects are more on maxE2500 batteries. Moreover, their estimated values are much different from measured ones for GP2100 and maxE2500. This might be caused by error in
estimating full capacity and capacity loss. Furthermore, current consumption may not accurate since the calculation is based on datasheet which is for 3V of Vdd and 25 °C. In the other way, our estimated values are close to the measured values. Their accuracy is normally in the range of ± 1-10 minutes (0-1%) for E1300, while it is ± 1-30 minutes (0-2.5%) for GP2100 and maxE2500. The different range of accuracy might be due to battery aging since an older battery can produce inconsistent power. Moreover, an error on estimation might be caused by number of charge cycles, and the accuracy of battery voltage and temperature measurements.

Table 1: Mapping of nodes, batteries and programmes

<table>
<thead>
<tr>
<th>Node</th>
<th>Battery(Aging)</th>
<th>Programme</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node1</td>
<td>GP2100(&gt;24 months)</td>
<td>P1(send 50 bytes/3 seconds)</td>
</tr>
<tr>
<td>Node2</td>
<td>MaxE2500(12-24 months)</td>
<td>P2(send 100 bytes/6 seconds)</td>
</tr>
<tr>
<td>Node3</td>
<td>E1300(6-12 months)</td>
<td>P3(send 50 bytes/6 seconds)</td>
</tr>
</tbody>
</table>

Table 2: Time (millisecond) spent in each state of each programme

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
</tr>
</thead>
<tbody>
<tr>
<td>TX</td>
<td>38.75</td>
<td>35.00</td>
<td>19.38</td>
</tr>
<tr>
<td>RX</td>
<td>2011.25</td>
<td>2038.13</td>
<td>2011.25</td>
</tr>
<tr>
<td>CPU-ACTIVE</td>
<td>1042.50</td>
<td>924.38</td>
<td>950.63</td>
</tr>
<tr>
<td>CPU-LOW</td>
<td>57950.00</td>
<td>57926.88</td>
<td>57969.38</td>
</tr>
<tr>
<td>SENSING</td>
<td>0.39</td>
<td>0.39</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Fig. 1: Comparison between Measured [blue], Calculated Lifetime by Equation (1)[red] and Proposed Equation [green] with Different Starting Voltages and Temperatures of Node1-GP2100 (a), Node2-maxE2500 (b) and Node3-E1300(c)

5. Conclusion and Future Work

Lifetime of node depends on battery capacity and current consumption of node. Temperature is one of key factors affecting the lifetime of sensor node since it increases both battery capacity and current consumption. This paper proposes equations to estimate node lifetime with different starting voltages and temperatures. All constant factors can be obtained by using real experiments. The results show that node lifetime can be predicted for different brands, capacities, ages of NiMH batteries and programmes. However, it does not include other factors which may affect battery capacity, such as charging techniques and number of charge cycles. Finally, this technique is proposed for predicting static load behaviour of one sender node on a single-hop network; therefore, it should be extended for real multi-hop environment with many nodes.

6. References

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