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Analysis Of Energy Demand Profile And Battery Lifespan For A Battery-Powered Sensor Node Employed In Monitoring Vibration Energy On A Machinery

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Abstract— **In this paper, analysis of energy demand profile and battery lifespan for a battery-powered sensor node employed in monitoring vibration energy on a machinery is presented. A four mode energy consumption model is adopted for the sensor node, where the modes are sleep mode, measure data mode, transmit data mode and receive data mode. A numerical example is based on the wireless sensor node used in monitoring both the energy and other information about the vibrations on a machinery using accelerometer-based algorithm. The data on the measurement mode is presented for two cases, one, when 512 data samples are taken, which is the minimum sample for acceptable accuracy. However, for high accuracy, the 512 data samples are taken four times and hence, the measurement time in this case is four times that of case one. The Tenergy T26B 18650 Li-Ion battery with capacity of 2600mAh is used in the analysis. The results showed the duty cycle for the two cases are respectively 0.9% for the high accuracy sampling and 0.28 for the low accuracy sampling with a cycle time of 720000 ms. Also, for the case of high accuracy sampling, in each cycle, the sensor node consumed 2.79 mJ in the measurement and process data mode, 38.964 mJ in the transmit data mode, 9.9 mJ in the receive data mode, and 10.70277 mJ in the sleep mode, giving a total of 62.35677 mJ per cycle and 7482.812 mJ per day. For the case of high accuracy sampling, the battery life is 90,062.4 hours or 10.27 years if the usable battery capacity is 100 % of its rated capacity. However, the battery life is 76,553.0 hours or 8.73 years if the usable battery capacity is 85 % of its rated capacity. This gives about 15% reduction in battery lifespan for a 15 % reduction in usable battery capacity. In all, the results showed the transmit data mode followed by the sleep mode are the high energy consuming modes which will require optimization for battery lifespan.**

Keywords— Battery Lifespan, Energy Demand Profile, Sensor Node, Usable Battery Capacity, Wireless Sensor, Energy Consumption Model

1. Introduction

Nowadays, there is growing adoption of wireless sensor devices and wireless sensor networks [1,2, 3,4, 5,6,7, 8,9,10,11,12,13,14,15]. This has given rise to Internet of Things (IoT), a network where 'things' or 'anything' that is adequately equipped with the facilities to connect and communicate electronically can become part of a network that range from a local area network to the world wide web of networks [16,17,18,19,20,21,22,23]. In such cases, sensor provides the requisite electronic capability for sensing the environment or monitoring specific actions or phenomena and also be able to process and store the data electronically using a local micro-controller-based system attached to the sensor [24,25,26,27,28,29,30]. In most cases, the sensors are also equipped with transceiver devices that enables the sensor node to connect and transmit and receive data and control information within a network [31,32,33,34,35,36,37].

In view of the salient features of modern sensor devices, they are increasingly being employed in various automation processes, remote data collection, remote monitoring and control of process as well as for smart systems implementation [38,39,40,41,42,43]. Essentially, sensors are getting more sophisticated with more features and hence the role of sensor node in a given system is becoming paramount to the effective functioning of the entire system. In view of this, ensuring effective function of the sensors at all times in the lifecycle of a sensor network or sensor-based IoT system is gaining more attention among researcher.

Generally, sensor nodes are resource constrained; they have limited memory, limited processing capabilities and also they are most often battery-powered in which case their battery life span is limited

[44,45,46,47]. In such case, determination of the power consumption profile of the sensor node and the lifespan of the battery are essential in managing the sensor-dependent system. Accordingly, in this paper, analysis of energy demand profile and battery lifespan for a battery-powered sensor node employed in monitoring vibration energy on a machinery is presented. The detailed analytical models for characterising the energy demand profile and battery lifespan are presented along with numerical examples that demonstrated the applicability of the models.

2. Methodology

2.1 Battery Lifespan Computation

The battery lifespan of a battery-powered sensor node is simply the duration of time that the fully charged battery delivering energy to the sensor node will last before it needs to be replaced. The analytical approach used to define the battery lifespan requires the following input parameters;

I_{SLP} denotes the current in mA drawn by the device when it is in its sleep mode

I_{TX} denotes the current in mA drawn by the device when it is in transmit mode

I_{RX} denotes the current in mA drawn by the device when it is in Receive mode

I_{MEAS} denotes the current in mA drawn by the device when it is in measurement mode

T_{TX} denotes the duration in mA that device is in Transmit (TX) mode

T_{RX} denotes the duration in mA that device is in Receive (RX) mode

T_{MEAS} denotes the duration in mA that device is in measurement mode

Now, let T_{ACT} denote the duration in mA that device is in active mode, then;

$$T_{ACT} = T_{TX} + T_{RX} + T_{MEAS} \quad (1)$$

n_{ACT} denotes the number of times per day the device will be in active mode

C_{Bat} denotes the capacity of the battery expressed in mAh

CUP_{Bat} denotes the usable battery capacity (expressed in %) after accounting for self-discharge

CU_{Bat} denotes the usable battery capacity (expressed in mAh) after accounting for self-discharge , where;

$$CU_{Bat} = C_{Bat}\left(\frac{CUP_{Bat}}{100}\right) (2)$$

Let T_{sHR} denote the number of milliseconds per hour which is $T_{sHR} = 3{,}600{,}000$

Let CA_{Day} denote the battery capacity used per day in the active mode of the device

Let CS_{Day} denote the battery capacity used per day in the sleep mode of the device

Let CTA_{Day} denote the total battery capacity used per day in both the active and sleep modes of the device and I_{AVGHR} denote the average current drawn per hour

$$CA_{Day} = \frac{n_{ACT}\{(T_{TX}*I_{TX}) + (T_{rX}*I_{rX}) + (T_{MEAS}*I_{MEAS})\}}{T_{sHR}} (3)$$

$$CS_{Day} = I_{SLP}\left(24 - \left(\frac{n_{ACT}(T_{TX} + T_{rX} + T_{MEAS})}{T_{sHR}}\right)\right) (4)$$

$$CTA_{Day} = CA_{Day} + CS_{Day} \quad (5)$$

$$I_{AVGHR} = \frac{CTA_{Day}}{24(T_{sHR})} = \frac{(CA_{Day} + CS_{Day})}{24(T_{sHR})} \quad (6)$$

C_{LFHR} denotes the battery lifespan expressed in hours

C_{LFDY} denotes the battery lifespan expressed in days

C_{LFYR} denotes the battery lifespan expressed in years

$$\text{Battery lifespan in hours, } C_{LFHR} = \left(\frac{CU_{Bat}}{I_{AVGHR}}\right) = \left(\frac{CU_{Bat}}{CA_{Day} + CS_{Day}}\right)((24)(T_{sHR}))(7)$$

$$\text{Battery lifespan in days, } C_{LFDY} = \left(\frac{CU_{Bat}}{I_{AVGHR}}\right)\left(\frac{1}{24}\right) = \left(\frac{CU_{Bat}}{CA_{Day} + CS_{Day}}\right)(T_{sHR}) \quad (8)$$

$$\text{Battery lifespan in year, } C_{LFYR} = \left(\frac{C_{LFDY}}{365.24}\right) = \left(\frac{CU_{Bat}}{CA_{Day} + CS_{Day}}\right)\left(\frac{T_{sHR}}{365.24}\right) \quad (9)$$

2.2 The Duty Cycle and Energy Demand Profile

The duty cycle defines the fraction of the cycle time that is used in the active mode of the sensor node. The time for one cycle, denoted as T_{Period} is the sum of one active mode time, T_{ACT} and sleep mode time, T_{SLP} where;

$$T_{Period} = \left(\frac{24*60*60*1000)\text{ms/day}}{120 \text{ active modes per day}}\right) = \left(\frac{24*T_{sHR})\text{ms/day}}{120 \text{ active modes per day}}\right) \quad (10)$$

Hence,

$$T_{SLP} = T_{Period} - T_{ACT} \quad (11)$$

The duty cycle, D_{Cyc} is given as;

$$D_{Cyc} = \left(\frac{T_{ACT}}{T_{Period}}\right) \ 100\ \% \quad (12)$$

The energy demand profile of the sensor node entails the energy the sensor node consumes in each of the modes it has per cycle. The energy profile is computed from the knowledge of the current, time and operating voltage of the sensor node in each of the modes. Assuming the operating voltage of V_{op}, the energy consumed by the sensor node in each mode per cycle are given as follows (where current is in mA, time is in second voltage is in V and then the energy is in mJ) ;

For the measurement mode, E_{MEAS}

$E_{MEAS} = T_{MEAS} * I_{MEAS} * V_{op}$ (13)

For the transmit data mode, E_{TX}

$E_{TX} = T_{TX} * I_{TX} * V_{op}$ (14)

For the receive data mode, E_{RX}

$E_{RX} = T_{RX} * I_{RX} * V_{op}$ (15)

For the active mode time, E_{ACT}

$E_{ACT} = E_{MEAS} + E_{TX} + E_{RX}$(16)

For sleep mode time, T_{SLP} , E_{SLP}

$E_{SLP} = T_{SLP} * I_{SLP} * V_{op}$ (17)

For each cycle, E_{Period}

$E_{Period} = E_{MEAS} + E_{TX} + E_{RX} + E_{SLP} = E_{ACT} + E_{SLP}$(18)

3. Numerical Example

The numerical example is based on the wireless sensor node used in monitoring both the energy and other information about the vibrations on a machinery using accelerometer-based algorithm, as presented by Magno, et al. in [47]. Specifically, a three-axis accelerometer, CMA3000-D01 from Murata, is interfaced with a microcontroller , MSP430 from Texas Instruments. Also, a nano-power wake-up radio is used to minimize energy drawn during idle period. The entire sensor node is built around the CC2530 system-on-chip which is responsible for communication with the ZigBee protocol that runs on the MSP430 microcontroller. In all, the energy consumption model adopted in [27] can be matched with the four distinct modes of the sensor node as presented in Table 1 [27] . The data in Table 1 are empirically measured current consumption for the four modes of the sensor node operating at 3V [27] . In Table 1, the data on the measurement mode is presented for two cases, one, when 512 data samples are taken, which is the minimum sample for acceptable accuracy. However, for high accuracy, the 512 data samples are taken four times and hence, the measurement time in this case is four times that of case one, as presented in Table 1.

Table 1. The energy consumption data adopted in [27] for the four distinct modes of the sensor node

S/N		Current (mA)	Time (s)
Sleep	Node sleep and wake-up	0.005	To be calculated
Measurement	Data acquisition and processing for 512 data samples	0.155	1.5
	Data acquisition and processing for 512 x4 data samples	0.155	6
Transmit MODE	Transmission of data	34	0.382
Receive Mode	Receive data	33	0.1

4. Result and Discussion

In this paper, the energy demand profile and the required battery capacity are computed using the energy consumption data presented in Table 1. Particularly, the period is determined from the number of times (n_{ACT}) the sensor node is expected to be in active mode per day. With $n_{ACT} = 120$ per day, the period is given as (24 *60*60)/ n_{ACT} = (24 *60*60)/ 120 = 720 s = 720000 ms. In the case of battery life determination, the selected battery capacity is the rechargeable Tenergy T26B 18650 Li-Ion battery with capacity of 2600mAh. The results of the computation for the active mode time, the sleep mode time, the cycle time and the duty cycle of the sensor node are shown in Table 2. The duty cycle for the two cases are respectively 0.9% for the high accuracy sampling and 0.28 for the low accuracy sampling with a cycle time of 720000 ms.

The results of the computation for the energy demand profile of the sensor node mode are given in Table 3 and Table 4. According to the results in Table 3 and Table 4, for the case of high accuracy sampling, in each cycle, the sensor node consumed 2.79 mJ in the measure and process data mode, 38.964 mJ in the transmit data mode, 9.9 mJ in the receive data mode, and 10.70277 mJ in the sleep mode, giving a total of 62.35677 mJ per cycle and 7482.812 mJ per day. The highest energy per cycle demand is in the transmit data mode followed by the sleep mode. As such, energy efficiency can be effectively pursued by optimizing the energy consumption in the two modes. On the other hand, for the case of low accuracy sampling, in each cycle, the sensor node consumed similar energy except in the measure and process data mode, where it consumed 0.6975 mJ per cycle instead of 2.79 mJ. Also, for the case of low accuracy sampling, in the sleep mode it consumed 10.77027 mJ per cycle instead of 10.70277mJ.

The results for the battery lifespan (in Table 5) show that for the case of high accuracy sampling, the battery life is 90,062.4 hours or 10.27 years if the usable battery capacity is 100 % of its rated capacity. However, the battery life is 76,553.0 hours or 8.73 years if the usable battery capacity is 85 % of its rated capacity. This gives about 15% reduction in battery lifespan for a 15 % reduction in usable battery capacity. Similarly, for the case of low accuracy sampling, the battery life is 93,085.3 hours or 10.62 years if the usable battery capacity is 100 % of its rated capacity. However, the battery life is 79,122.5 hours or 9.03 years if the usable battery capacity is 85 % of its rated capacity. Again, this amounts to about 15% reduction in battery lifespan for a 15 % reduction in usable battery capacity.

Table 2 The results of the computation for the active mode time, the sleep mode time, the cycle time and the duty cycle of the sensor node, with $n_{ACT} = 120$ per day.

For the case of high accuracy sampling with 512 x 4 samples			
Time spent in active mode	**Time spent in sleep mode**	**Time spent in one cycle**	**Duty Cycle**
T_{ACT} **(ms)**	T_{SLP} **(ms)**	T_{Period} **(ms)**	D_{Cyc} **(%)**
6482	713518	720000	0.90
For the case of low accuracy sampling with 512 x 1 samples			
Time spent in active mode	**Time spent in sleep mode**	**Time spent in one cycle**	**Duty Cycle**
T_{ACT} **(ms)**	T_{SLP} **(ms)**	T_{Period} **(ms)**	D_{Cyc} **(%)**
1982	718018	720000	0.28

Table 3 The results of the computation for the energy demand profile of the sensor node mode

For the case of high accuracy sampling with 512 x 4 samples					
Sensor Node Mode	**Current per cycle, I (mA)**	**Time per cycle, t (mS)**	**Power per cycle, P (mW)**	**Energy per cycle,** E_{Period} **(mJ)**	**Energy per day ,** E_{day} **(mJ)**
Transmit	**34**	**382**	**102**	**38.964**	**4675.68**
Receive	**33**	**100**	**99**	**9.9**	**1188.00**
Measure	**0.155**	**6000**	**0.465**	**2.79**	**334.80**
Sleep	**0.005**	**713518**	**0.015**	**10.70277**	**1284.33**
Total				**62.35677**	**7482.812**
For the case of low accuracy sampling with 512 x 1 samples					
Sensor Node Mode	**Current per cycle, I (mA)**	**Time per cycle, t (mS)**	**Power per cycle, P (mW)**	**Energy per cycle,** E_{Period} **(mJ)**	**Energy per day ,** E_{day} **(mJ)**
Transmit	**34**	**382**	**102**	**38.964**	**4675.68**
Receive	**33**	**100**	**99**	**9.9**	**1188.00**
Measure	**0.155**	**1500**	**0.465 l;**	**0.6975**	**83.70**
Sleep	**0.005**	**718018**	**0.015**	**10.77027**	**1292.43**
Total				**60.33177**	**7239.812**

Table 4 Normalised energy demand with respect energy demand per cycle, E_{Period}

For the case of high accuracy sampling with 512 x 4 samples									
E_{TX} **(mJ)**	E_{RX} **(mJ)**	E_{MEAS} **(mJ)**	E_{ACT} **(mJ)**	E_{SLP} **(mJ)**	E_{Period} **(mJ)**	E_{hr} **(mJ)**	E_{day} **(mJ)**	E_{year} **(mJ)**	
39.0	**9.9**	**2.8**	**51.7**	**10.7**	**62.4**	**311.8**	**7482.8**	**2733022.4**	
62.5 %	**15.9 %**	**4.5 %**	**82.8 %**	**17.2%**	**100.0 %**	**500.0%**	**12000.0%**	**4382880.%0**	**Percentage of E_{Period}**
E_{BAT} **(mJ) =28080000 mJ**									
For the case of low accuracy sampling with 512 x 4 samples									
E_{TX} **(mJ)**	E_{RX} **(mJ)**	E_{MEAS} **(mJ)**	E_{ACT} **(mJ)**	E_{SLP} **(mJ)**	E_{Period} **(mJ)**	E_{hr} **(mJ)**	E_{day} **(mJ)**	E_{year} **(mJ)**	E_{BAT} **(mJ)**
39.0	**9.9**	**0.7**	**49.6**	**10.8**	**60.3**	**301.7**	**7239.8**	**2644269.1**	
62.5 %	**15.9 %**	**4.5 %**	**82.8 %**	**17.2%**	**100.0 %**	**500.0%**	**12000.0%**	**4382880.%0**	**Percentage of E_{Period}**

Table 5 Battery Lifespan based on the energy demand profile of the sensor node mode

For the case of high accuracy sampling with 512 x 4 samples						
	Average Current Drawn Per Hour	Usable Battery Capacity	Affective Battery Capacity	Battery Lifespan in Hours	Battery Lifespan in Days	Battery Lifespan in Years
	I_{AVGHR} *(mA)*	CUP_{Bat} *(%)*	CU_{Bat} *(mAh)*	C_{LFHR} $(hours)$	$C_{LFDY}(day)$	C_{LFYR} $(year)$
1	0.028868875	100	2,600.0	90,062.4	3752.60	10.27
2	0.028868875	85	2,210.0	76,553.0	3189.71	8.73
For the case of low accuracy sampling with 512 x 1 samples						
	Average Current Drawn Per Hour	Usable Battery Capacity	Affective Battery Capacity	Battery Lifespan in Hours	Battery Lifespan in Days	Battery Lifespan in Years
	I_{AVGHR} *(mA)*	CUP_{Bat} *(%)*	CU_{Bat} *(mAh)*	C_{LFHR} $(hours)$	$C_{LFDY}(day)$	15
1	0.027931375	100	2,600.0	93,085.3	3878.55	10.62
2	0.027931375	85	2,210.0	79,122.5	3296.77	9.03

5. Conclusion

The analytical models for computing the energy demand profile and battery lifespan of a battery-powered sensor node are presented. The case study sensor node is used for monitoring vibration energy in a machinery. The empirically measure current and timing values for the various sensor node operating modes are used for a numerical example. The results showed the transmit data mode followed by the sleep mode are the high energy consuming modes which will require optimization for optimal battery lifespan.

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