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# Energy Level Analysis For Lorawan-Based Sensor Node With Solar Energy Harvester And Battery Storage

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***Abstract*— In this paper, energy level analysis for LoRaWAN-based sensor node with solar energy harvester and battery storage is presented. The energy level analysis entails determination of the average current of a sensor node, the required battery that can supply energy to the sensor node and the solar cell size for the energy harvest. Based on these computed parameters, the daily energy level of the battery is analyzed to determine the daily energy balance for the sensor node power supply. Hence, it can be determined when there will be power outage in the sensor node. The study was conducted using the daily solar irradiation for a location in Port Harcourt, Rivers State with annual mean value of 4039.5 W/ $m^2$ /day. The average current, $I_{AVG}$ was computed with the following input parameter values; $I_{ACT}$ = 199.5 mA, $t_{ACT} = 1.2$ s , $I_{SLP} = 0.0075$ mA and $t_{SLP} = 10.8$ s and the results was $I_{AVG}$ = 19.95675 mA $\approx 20$ mA. Also, with the following parameter values D =3 days, $S_B$ =1.2 , $C_u$= 0.9 , $C_T$ = 0.95 and $\eta_c$ = 0.97, the battery capacity, $C_B$ required to power the sensor node was computed to be $C_B = 2083.559414\, mAh \approx 2084 mAh$. Again, with Gt =4039.5 W/ $m^2$ /day, $t_f = 2\ days, V_s = 6\ V, S_s$ =1.2 and $\eta_s = 0.15$ the energy the solar cell will store in the battery per day, $E_R$=50.016 Wh and the solar cell area that will be required for that amount of solar energy harvest per day was $A_s$ =0.012382 $m^2$ $\approx 124\ cm^2$. The effect of days of autonomy settings on the energy balance and power outage in the sensor node is also presented. In all, lower days of autonomy will increase the percentage of days in a year with power outage whereas higher value of days of autonomy will reduce the days of power outage. However, increasing the days of autonomy will increase the required battery capacity and also results in higher amount of lost energy. As such, optimal selection of the days r hours of autonomy, D = 3.132 was selected to avoid waste of money in buying higher capacity battery that will amount to high amount of energy lost.**

***Keywords* — *Solar Energy, Sensor Node, Energy Level Analysis, LoRaWAN, Smart City, Energy Harvest***

## 1. Introduction

Nowadays, the quest for green and smart technologies is driving researchers and experts to innovate renewables energy-powered solutions that support smart applications [1,2,3,4,5,6]. In this wise, the wireless communication industry has been at the fore front of developing wireless sensor technologies that can effectively drive smart solutions [7,8,9,10,11,12,13,14,15,16,17,18,19,20,21]]. Such technologies as wireless sensor networks have already become popular in the terrestrial wireless applications and there is now efforts to develop satellite-based wireless sensor communication links whereby, the low-power sensor nodes can communicate directly with the satellite [22,23,24,25,26,27,28,29]. The emerging technology will greatly fast track deployment of globally distributed smart solutions.

In any case, the key challenges for wireless signal includes the diverse signal strength degradation mechanisms that tend to attenuate and distort the wireless signal as it propagates from the transmitter to the receiver [30,31,32,33, 34,35,36,37, 38,39,40,41,42, 43]. The attenuation problem is also a key challenge for wireless sensor networks [,44,45,46,47, 48,48,50,51 52,53,54,55,56,57,58] as the sensor nodes are in most cases power-constrained and hence require additional measures to sustain the power supply for the required network communication range and network lifetime. Also, due to certain regional restrictions on the transmission power and related parameters of the sensor nodes, the possible transmission range of the sensor nodes are greatly limited [59,60,61,62,63,64,65]. However, LoRaWAN is one of the most promising long range and low power wireless technologies which has been employed for different wireless sensor-based applications across the globe. Due to its wide applications, researchers are developing solutions to enhance the performance of LoRaWAN-based solutions [66,67,68,69,70,71].

In this paper, the focus is on the energy level analysis for LoRaWAN-based sensor node with solar energy harvester and storage battery [72,73,74,75,76]. The study seek to provide means of determining at design time the daily energy harvested and stored for powering the sensor node in a LoRaWAN-based sensor network. The idea is to ensure that power outage can be mitigated at the design time without oversizing the solar cell and storage battery which will amount to excess cost in the deployment of the sensor network. This is important because, in most cases, the sensor nodes are deployed in large numbers and any access cost adds up to a substantial amount in the overall network deployment cost. In all, the study used a case study daily solar irradiation data and other requisite data items to demonstrate the applicability of the ideas presented in this paper.

## 2. Methodology

The energy level analysis entails determination of the average current of a sensor node, the required battery that can supply energy to the sensor node and the solar cell size for the energy harvest. Based on these computed parameters, the energy level of the battery is analyzed to determine the daily energy balance for the sensor node power supply. Hence, it can be determined when there will be power outage in the sensor node. The list of parameters used in the analysis and their descriptions, symbols and input values are presented in Table 1.

Table 1 List of parameters and their descriptions, symbols and input values

| S/N | Parameter Symbol | Parameter Description | Parameter input value |
|---|---|---|---|
| 1 | $I_{ACT}$ | current in the active mode | **199.5 mA** |
| 2 | $t_{ACT}$ | time spent in the active mode | **1.2 s** |
| 3 | $I_{SLP}$ | current in the sleep | **0.0075 mA** |
| 4 | $t_{SLP}$ | time spent in the sleep mode respectively | **10.8 s** |
| 5 | $I_{AVG}$ | average current | |
| 6 | $\eta_c$ | Charge efficiency, | 97% |
| 7 | $C_u$ | Useable battery capacity | 90% |
| 8 | $C_T$ | Temperature dependent capacity | 95% |
| 9 | D | Number of days without solar irradiation | 3 |
| 10 | $S_B$ | Battery capacity sizing Safety factor | 1.2 |
| 11 | $C_B$ | Battery capacity, | |
| 12 | Gt | Average daily solar irradiation | 4039.5 W/$m^2$/day Obtained from the site dataset |
| 13 | $t_f$ | Time in days required for full charge | |
| 14 | $V_s$ | Solar cell rated voltage | 6 v |
| 15 | $S_s$ | Solar cell efficiency | 15 % |
| 16 | $S_s$ | Solar cell sizing safety factor | 1.2 |
| 17 | $E_R$ | Required solar energy | |
| 18 | $A_s$ | Required solar cell area | |
| 19 | $Gt_i$ | Daily solar irradiation on day i | Obtained from the daily solar irradiation data of the study site |
| 20 | $E_{R(i)}$ | Solar energy generated by solar cell with area $A_s$ and daily solar irradiation , $Gt_i$ | |
| 21 | $E_{RDay}$ | Daily energy demand from the sensor node in (Wh) | |
| 22 | $E_{RN(i)}$ | Net energy produced and consumed in day i, (Wh) | |
| 23 | $E_{R(FullBatCap)}$ | Energy stored in the battery when the battery is fully charged (Wh) | |
| | | | |

The parameters are computed using the following expressions;

$$I_{AVG} = \frac{I_{SLP}\,(t_{SLP}) + I_{ACT}(t_{ACT})}{t_{SLP} + t_{ACT}} \quad (1)$$

$$C_B = \frac{24(D)\,(I_{AVG})(S_B)}{(C_u)(C_T)(\eta_c)} \quad (2)$$

$$E_R = \frac{C_B(V_s)(S_s)}{(\eta_s)(t_f)} \quad (3)$$

$$A_s = \frac{E_R}{\mathrm{Gt}} \quad (4)$$

$$E_{R(i)} = (A_s)Gt_i \text{ , Gt where Gt for i = 0} \quad (5)$$

$$C_{B/day} = \frac{C_B}{D} \quad (6)$$

$$E_{R(FullBatCap)} = \left(E_{R_S}\right)\left(t_f\right) \quad (7)$$

$E_{RDay} = \frac{(C_{B/day})(V_s)(S_s)}{(\eta_s)}$ (8)

$E_{RN(i)} = E_{R(i)} - E_{RDay}$ (9)

Net of cumulative energy produced and consumed from the first day to the end of day i, $B_{RBatEN(i)}$ (Wh) if battery with infinite capacity is used. It is assumed that the battery is initially fully charged, hence, current energy stored in the battery at the beginning of day o (zero) $E_{RBatBG(0)}$ is given as;

$E_{RBatBG(0)} = E_{R(FullBatCap)}$(10)

$B_{RBatEN(0)} = E_{RBatBG(0)} + E_{R(0)} - E_{RDay}$ (11)

Net of cumulative energy stored in the battery in day i, $E_{RSBat(i)}$ (Wh) if battery with capacity $E_{R(FullBatCap)}$ is used is given as;

$E_{RSBatENLT(0)} = \text{minimum}(B_{RBatEN(0)}, E_{R(FullBatCap)})$(12)

The unused energy in day i, $E_{RUnUsed(0)}$

$E_{RUnUsed(0)} = \max\left(0, \left(B_{RBatEN(0)} - E_{RSBatENLT(0)}\right)\right)$ (13)

Then, for i > 0;

$E_{RBatBG(i)} = \max(0, E_{RSBatENLT(i-1)})$ (14)

$B_{RBatEN(i)} = E_{RBatBG(i)} + E_{R(i)} - E_{RDay}$ (11)

$E_{RSBatENLT(i)} = \text{minimum}(B_{RBatEN(i)}, E_{R(FullBatCap)})$(12)

$E_{RUnUsed(0)} = \max\left(0, \left(B_{RBatEN(i)} - E_{RSBatENLT(i)}\right)\right)$ (13)

Let, $n_{LoLD}$ denote the number of days that there is no energy in the battery to power the sensor node. This is the number of days in a year where $E_{RSBatENLT(i)} < E_{R(FullBatCap)}$. Then, the loss of load probability, LoLP is given in terms of

$LoLP = \left(\frac{n_{LoLD}}{365}\right) 100\,\%$(15)

### 2.2 The case study dataset

The study was conducted using the daily solar irradiation for a location in Port Harcourt, Rivers State. The irradiation data is part of the meteorological data extracted from NASA portal using PVSyst software and the PVSyst dialogue box showing the location of the meteorological data used in the study is shown in Figure 1 while the scatter plot of the daily solar irradiation for a year (365 days) is shown in Figure 2. The annual mean of the daily global irradiation on horizontal plane for the case study is 4039.5 W/$m^2$/day.

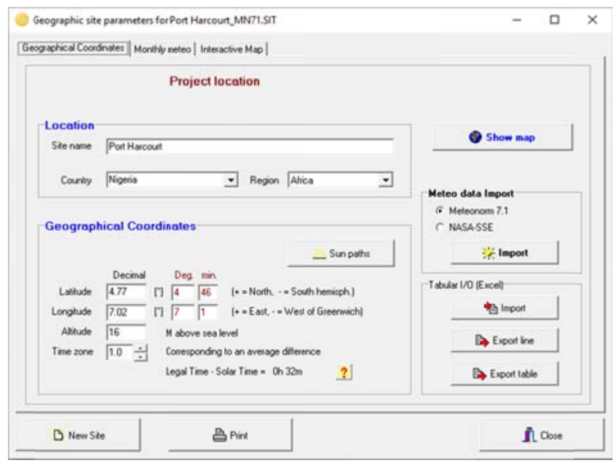


Figure 1 The PVSyst dialogue box showing the location of the meteorological data used in the study

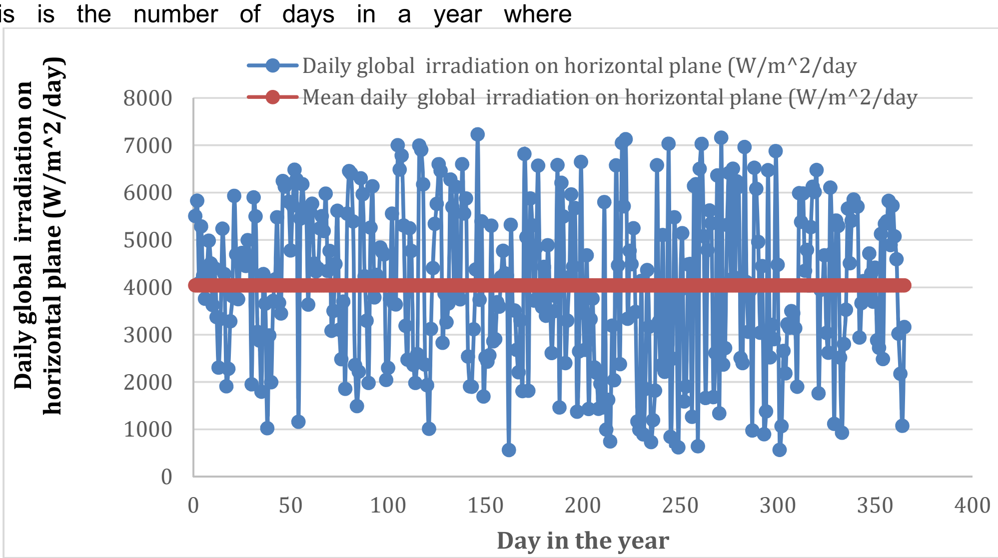


**Figure 2** The scatter plot of the daily global irradiation on horizontal plane (W/m^2/day) for one year

## 3. Results and discussion

The values in Table 1 are used in the computation of the various parameters. Particularly, the average current, $I_{AVG}$ was computed with the following input parameter values; $I_{ACT}$ = 199.5 mA, $t_{ACT}$ = 1.2 s , $I_{SLP}$ = 0.0075 mA and $t_{SLP}$ = 10.8 s and the results is $I_{AVG}$ = 19.95675 mA $\approx 20$ mA. Also, with the following parameter values D =3 days, $S_B$ =1.2 , $C_u$= 0.9 , $C_T$ = 0.95 and $\eta_c$ = 0.97 the battery capacity, $C_B$ required to power the sensor node is computed to be $C_B = 2083.559414\,mAh \approx 2084mAh$. Again, with Gt =4039.5 W/$m^2$/day, $t_f = 2\,days, V_s = 6\,V, S_s$ =1.2 and $\eta_s = 0.15$ the energy the solar cell will store in the battery per day, $E_R$=50.016 Wh and the solar cell area that will be required for that amount of solar energy harvest per day is $A_s = 0.012382\ m^2 \approx 124\,cm^2$. Since by the parameters selected, it takes $t_f = 2\,days$ to fully charge the battery, it means, at full charge, the battery will store 100.032 Wh of energy. Also, by the parameters, the fully charged battery will be able to sustain the sensor node for D =3 days, it means that the energy required to sustain the sensor node for one day is 33.344 Wh (that is 100.032 Wh/D). Essentially, the daily energy demand from the battery is 33.344 Wh.

The daily solar irradiation, $Gt_i$ on day i= 1 ,2,3,.,365 is used to compute $E_{R(i)}$, (that is, the daily energy harvested by the solar cell. Then the daily energy stored in the battery is computed and the results are plotted along with the daily energy demand, as shown in Figure 3. The information in Figure 3 is also captured in another form as the net battery stored energy with respect to daily energy demand (Wh), as shown in Figure 4. The results in Figure 3 and Figure 4 show that the net battery stored energy with respect to daily energy demand is negative in some days or put another way, the energy stored in the battery is less than the daily energy demand in some days. In such days, the sensor node will witness power outage or loss of load will occur. The whole year results showed that such outage or loss of load will occur in 4 days out of the 365 days in a year. This gives rise to a loss of load probability of 1.095890411 % $\approx 1.1$ %.

While there are few days with shortfall in energy from the required daily demand, there are also days when the energy harvested is so much that the battery is fully charged and there is no place to store the excess energy. Such excess energy are unused and hence lost. The daily net energy in day i and the unused (lost) energy in day I are shown in Figure 5. The results showed that there are 245 days of unused energy which is 67.12328767 % of the days in a year. Also, there are 116 days of unused energy which is 31.78082192 % of the days in a year. Increasing the days of autonomy, D to 3.5 days will reduce loss of load or outage days to 0 (zero) but the required battery capacity would have increased to 2431 mAh.

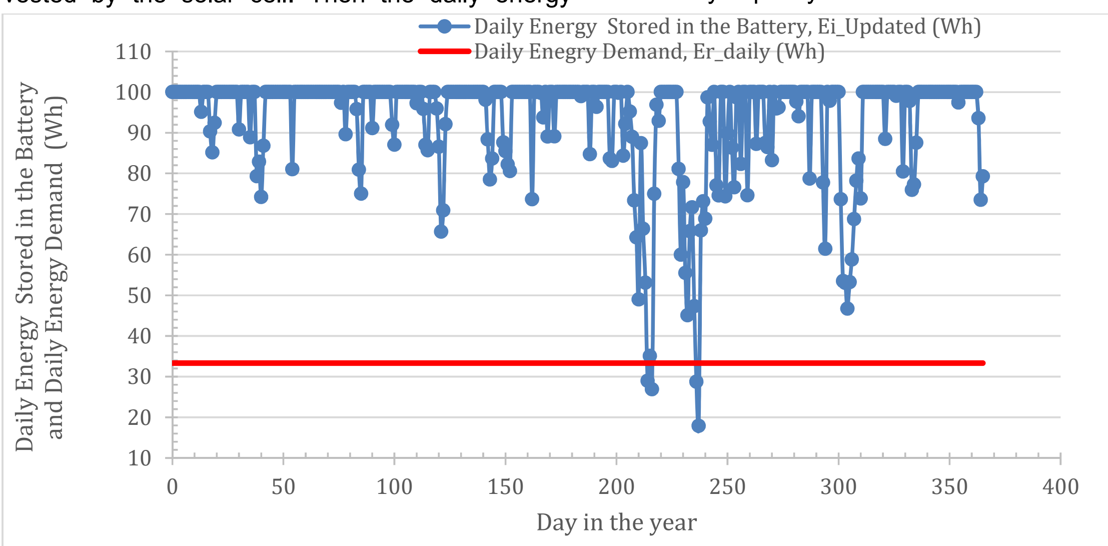


Figure 3 The daily energy stored in the battery is computed and the results are plotted along with the daily energy demand for 3 days of autonomy (D =3 ) and battery charging duration of 2 days ( $t_f = 2$)

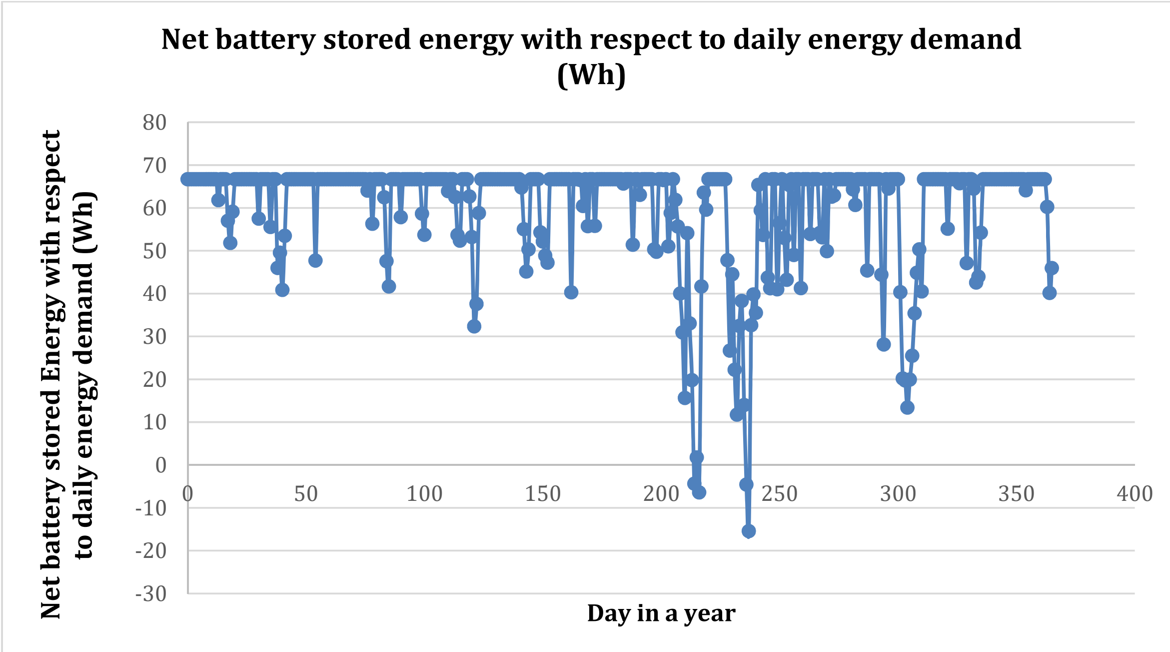


Figure 4 Net battery stored energy with respect to daily energy demand (Wh) for 3 days of autonomy (D =3 ) and battery charging duration of 2 days ( $t_f = 2$)

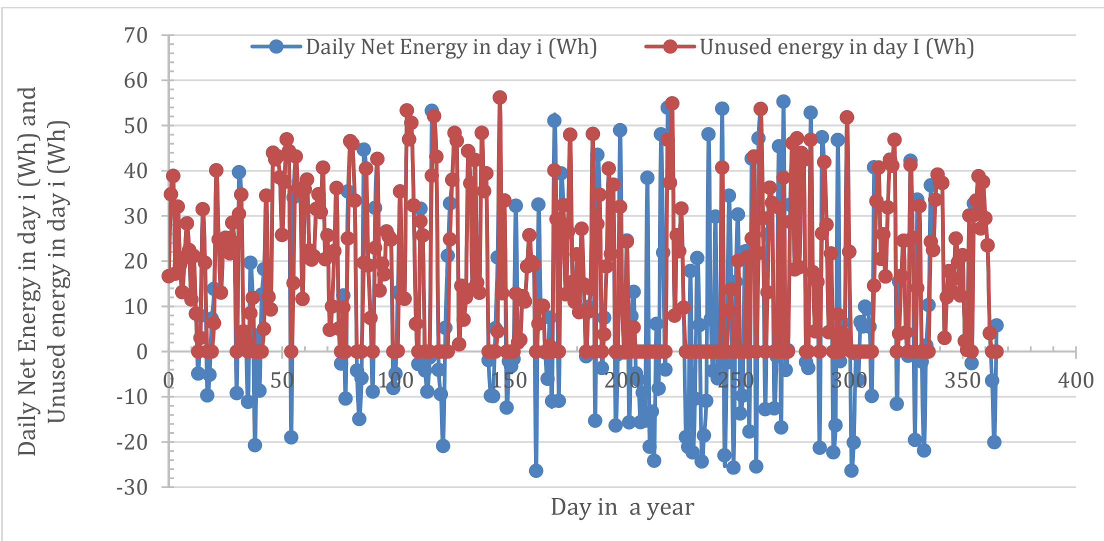


Figure 5 Daily net energy in day i (Wh) and unused energy in day i (Wh) for 3 days of autonomy (D =3 ) and battery charging duration of 2 days ( $t_f = 2$)

**Table 2 Summary of the key results of the computation for 3 days of autonomy (D =3 ) and battery charging duration of 2 days ( $t_f = 2$)**

| S/N | Parameter | Unit | Value |
|---|---|---|---|
| 1 | Average current | mA | 20.0 |
| 2 | Battery capacity required | mAh | 2084 |
| 3 | Solar cell area required | cm^2 | 124 |
| 4 | The daily energy demand from the battery | Wh | 33.344 |
| 5 | Energy store in fully charged battery | Wh | 100.032 |
| 6 | Number of days of power outage | Days | 4 |
| 7 | Percentage of days of power outage | % | 1.1 |
| 8 | Number of days of excess energy is unused or lost | Days | 245 |
| 9 | Percentage of days excess energy is unused or lost | % | 67.1 |
| 10 | Number of days of excess energy is completely stored | Days | 116.0 |
| 11 | Percentage of days excess energy is completely stored | % | 31.8 |

The results of the same sensor node but for 2 days of autonomy (D =2 ) and battery charging duration of 2 days ( $t_f = 2$) are shown in Figure 6, Figure 7 and Table 3. In this case, a smaller battery capacity of 1389 mAh is required. However, the percentage of days of power outage has increased from 1.1 % to 37.5 % which is about 137 days of down time in the system. On the other hand, the percentage of days excess energy is unused or lost reduced from 67.1 % to 18.4 %.

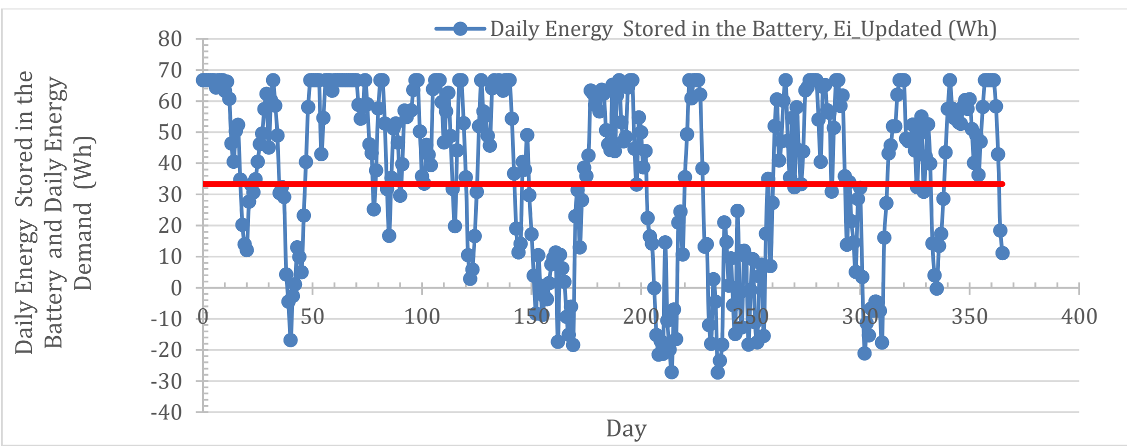


Figure 6 The daily energy stored in the battery is computed and the results are plotted along with the daily energy demand for 2 days of autonomy (D =2 ) and battery charging duration of 2 days ( $t_f = 2$)

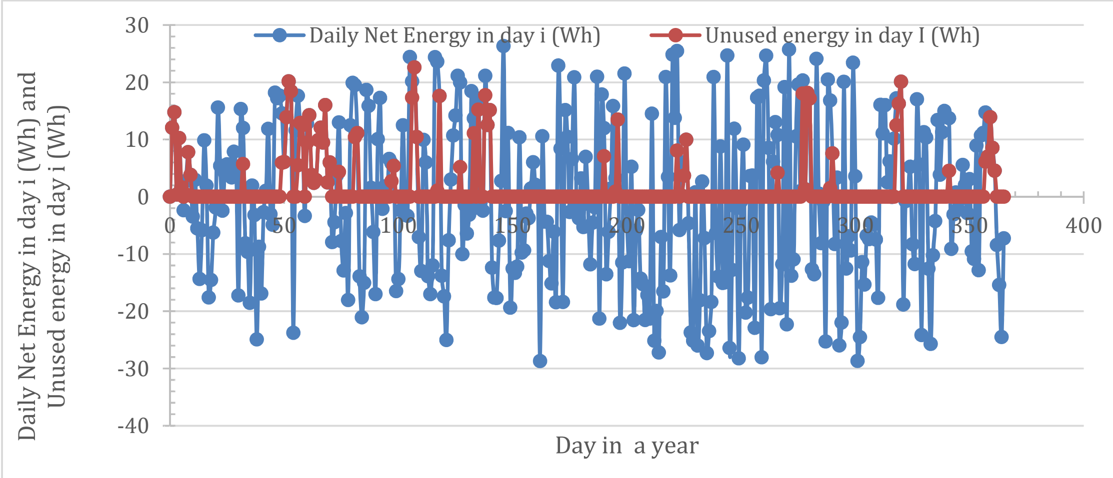


Figure 7 Daily net energy in day i (Wh) and unused energy in day i (Wh) for 2 days of autonomy (D = 2 ) and battery charging duration of 2 days ( $t_f = 2$)

**Table 3 Summary of the key results of the computation for 2 days of autonomy (D =2 ) and battery charging duration of 2 days ( $t_f = 2$)**

| S/N | Parameter | Unit | Value |
|---|---|---|---|
| 1 | Average current | mA | 20.0 |
| 2 | Battery capacity required | mAh | 1389 |
| 3 | Solar cell area required | cm^2 | 83 |
| 4 | The daily energy demand from the battery | Wh | 33.336 |
| 5 | Energy store in fully charged battery | Wh | 66.672 |
| 6 | Number of days of power outage | Days | 137 |
| 7 | Percentage of days of power outage | % | 37.5 |
| 8 | Number of days of excess energy is unused or lost | Days | 67 |
| 9 | Percentage of days excess energy is unused or lost | % | 18.4 |
| 10 | Number of days of excess energy is completely stored | Days | 161.0 |
| 11 | Percentage of days excess energy is completely stored | % | 44.1 |

Similarly, the results of the same sensor node but for 4 days of autonomy (D =4) and battery charging duration of 2 days ( $t_f = 2$) are shown in Figure 8, Figure 9 and Table 4. In this case, a larger battery capacity of 2778 mAh is required. However, the percentage of days of power outage has decreased from 0 % to 37.5 % which is no day of down time in the system. On the other hand, the percentage of days excess energy is unused or lost increased from 67.1 % to 82.7 %. In all, the choice of the battery capacity, the solar cell size for the same sensor node will significantly affect the energy balance and the power outage in the system.

**Table 4 Summary of the key results of the computation for 4 days of autonomy (D =4 ) and battery charging duration of 2 days ( $t_f = 2$)**

| S/N | Parameter | Unit | Value |
|---|---|---|---|
| 1 | Average current | mA | 20.0 |
| 2 | Battery capacity required | mAh | 2778 |
| 3 | Solar cell area required | cm^2 | 165 |
| 4 | The daily energy demand from the battery | Wh | 33.336 |
| 5 | Energy store in fully charged battery | Wh | 133.344 |
| 6 | Number of days of power outage | Days | 0 |
| 7 | Percentage of days of power outage | % | 0.0 |
| 8 | Number of days of excess energy is unused or lost | Days | 302 |
| 9 | Percentage of days excess energy is unused or lost | % | 82.7 |
| 10 | Number of days of excess energy is completely stored | Days | 63.0 |
| 11 | Percentage of days excess energy is completely stored | % | 17.3 |

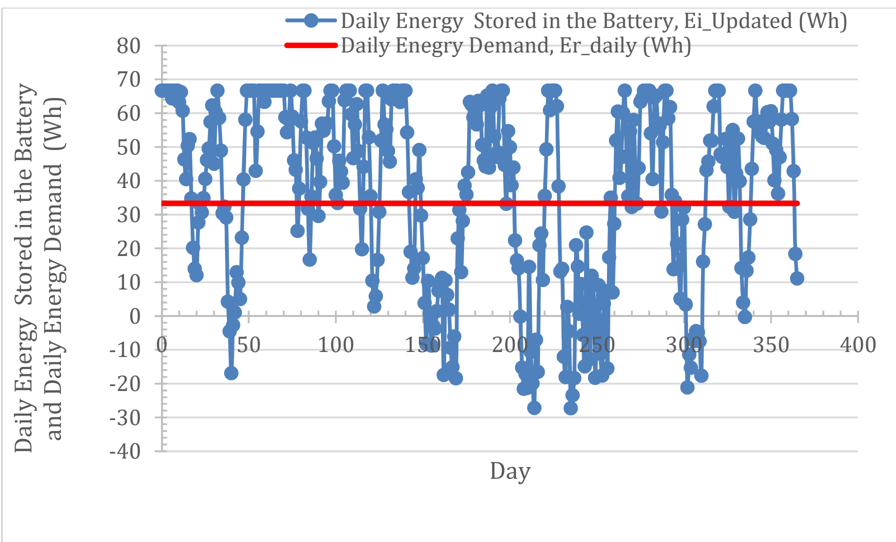


Figure 8 The daily energy stored in the battery is computed and the results are plotted along with the daily energy demand for 4 days of autonomy (D =4 ) and battery charging duration of 2 days ( $t_f = 2$)

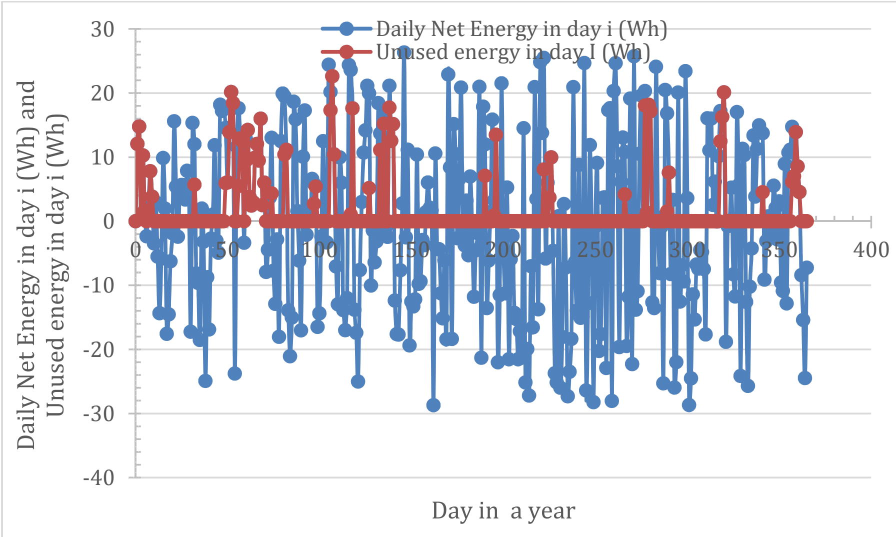


Figure 9 Daily net energy in day i (Wh) and unused energy in day i (Wh) for 4 days of autonomy (D = 4 ) and battery charging duration of 2 days ( $t_f = 2$)

In order to minimize the excess battery capacity to achieve zero power outage, a graph (Figure 10) is plotted for number of days of power outage in a year versus minimal number of days of autonomy (D = **3.132** ) and battery charging duration of 2 days ( $t_f = 2$). The zero days of autonomy is obtained with a minimal D of **3.132 days.** The results of the same sensor node but for **3.132** days of autonomy (D = **3.132**) and battery charging duration of 2 days ( $t_f = 2$) are shown in Figure 11, Figure 12 and Table 5. In this case, a larger battery capacity of 2778 mAh is required. However, the percentage of days of power outage has decreased from 0 % to 37.5 % which is no day of down time in the system. On the other hand, the percentage of days excess energy is unused or lost increased from 67.1 % to 82.7 %. In all, the choice of the battery capacity, the solar cell size for the same sensor node will significantly affect the energy balance and the power outage in the system.

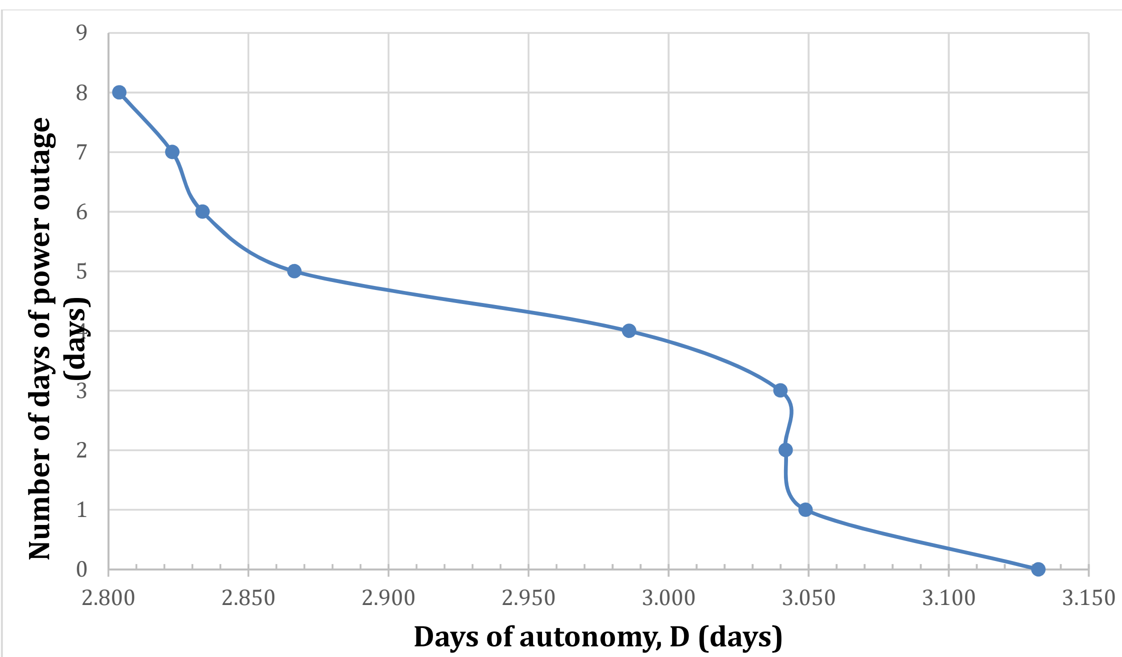


Figure 10 Number of days of power outage in a year versus minimal number of days of autonomy (D) and battery charging duration of 2 days ( $t_f = 2$)

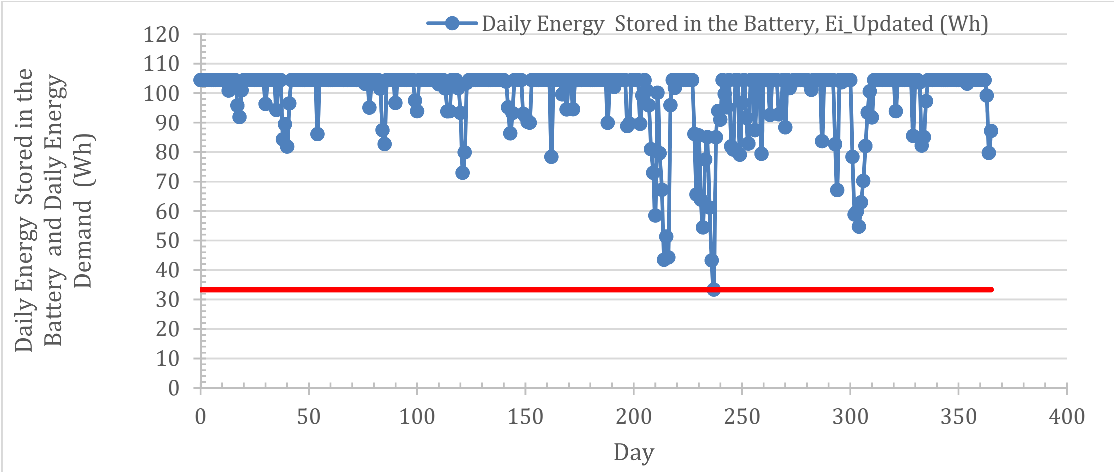


Figure 10 The daily energy stored in the battery is computed and the results are plotted along with the daily energy demand for **3.132** days of autonomy (D =**3.132** ) and battery charging duration of 2 days ( $t_f = 2$)

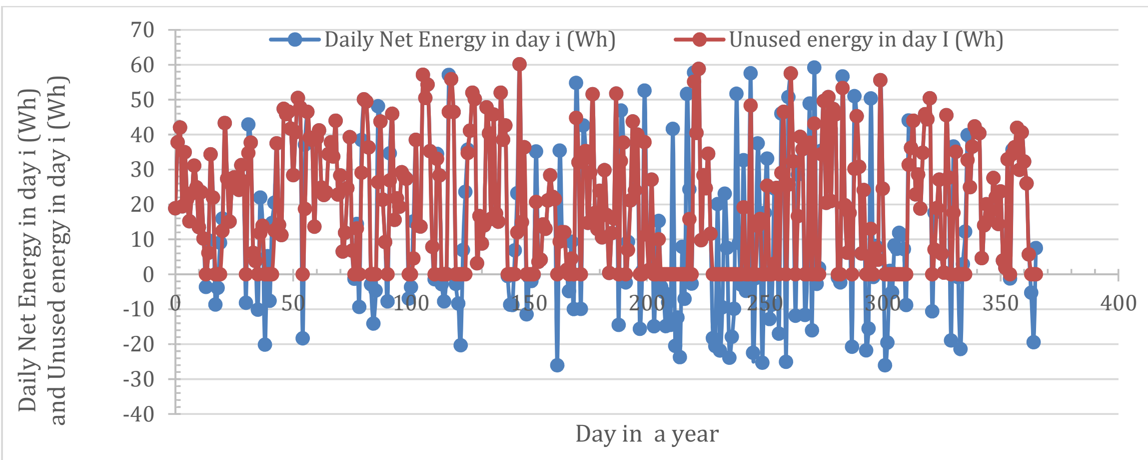


Figure 12 Daily net energy in day i (Wh) and unused energy in day i (Wh) for **3.132** days of autonomy (D = **3.132**) and battery charging duration of 2 days ( $t_f = 2$)

**Table 5 Summary of the key results of the computation for 3.132 days of autonomy (D =3.132) and battery charging duration of 2 days ( $t_f = 2$)**

| S/N | Parameter | Unit | Value |
|---|---|---|---|
| 1 | Average current | mA | 20.0 |
| 2 | Battery capacity required | mAh | 2176 |
| 3 | Solar cell area required | cm^2 | 129 |
| 4 | The daily energy demand from the battery | Wh | 33.348659 |
| 5 | Energy store in fully charged battery | Wh | 104.448 |
| 6 | Number of days of power outage | Days | 0 |
| 7 | Percentage of days of power outage | % | 0.0 |
| 8 | Number of days of excess energy is unused or lost | Days | 252 |
| 9 | Percentage of days excess energy is unused or lost | % | 69.0 |
| 10 | Number of days of excess energy is completely stored | Days | 113.0 |
| 11 | Percentage of days excess energy is completely stored | % | 31.0 |

## 4 Conclusion

Analysis of the daily energy level in the battery storage for sensor node with solar energy harvester is presented. The analysis considered the computation of various parameters, among which are the average current of the sensor node, the required battery capacity and the solar panel cell size required to harvest the energy and charge the battery. Also, the daily energy demand, the daily energy level of the battery and the unused (or lost) energy are computed along with power outage parameters. The effect of days of autonomy settings on the energy balance and power outage in the sensor node is also presented. In all, lower days of autonomy will increase the percentage of days in a year with power outage whereas higher value of days of autonomy will reduce the days of power outage. However, increasing the days of autonomy will increase the required battery capacity and also results in higher amount of lost energy. As such, optimal selection of the days or hours of autonomy is required to avoid waste of money in buying higher capacity battery that will amount to high amount of energy lost.

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