

Evaluation of energy demand and lifespan of battery-powered ZigBee IEEE 802.15.4 compliant sensor node for Internet of Things-based applications

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Abstract— In this paper, evaluation of energy demand and lifespan of battery-powered ZigBee IEEE 802.15.4 compliant sensor node for Internet of Things-based applications is presented. The sensor node energy consumption is modelled with four states, namely; transmit, receive, measure and sleep state. The sensor node runs in each of the four states in each cycle with a given cycle time and duty cycle. Mathematical model for computing the energy consumed in each of the states and the battery lifespan and other relevant parameter are presented. Specifically, the energy consumption parameters of Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node was used for the case study numerical computations. The results show that with duty cycle of 1 %, the data capture (measure) state has the highest energy consumption of 66.96 mJ per cycle followed by the transmit state with per cycle energy consumption of 40.6377 mJ. The energy consumed per day is 27464.2 mJ and the battery lifespan is 22,084 hours and in this lifespan the sensor node would have run 195,581 cycles and transmitted a total of 16,819,925 bits of data if it transmits 86 bits per cycle. Als, the results show that if active states time and current parameter values are maintained while the duty cycle is increased, the battery lifespan decreases but the number of bits transmitted over the battery lifespan increases. This is due to rapid increase in the number of cycles per day with increase in duty cycle is increased. Also, the energy consumption per day increases with increase in the duty cycle. In all, the specific impact of increase in the duty cycle on the energy consumption of the sensor node depends on which parameters are kept constant and which ones are varied.

Keywords— Energy Demand, Sensor Node, Battery Lifespan, ZigBee , Internet of Things, IEEE 802.15.4

1. Introduction

In recent years, smart applications are increasingly being adopted across the globe [1,2, 3,4, 5, 6, 7,8,9]. The growing smart application industry relies on robust wireless sensors [10,11,12,13,14,15,16,17,18,19]. The sensors on their own are basically meant to capture parameters of their immediate environment and possibly store the data or allow the data to be accessed and utilised in other sub-units of the system [20,21,22,23,24,25,26,27,28,29]. In more advanced sensor nodes, additional functionalities are incorporated, such as transceiver and microcontroller that can enhance the capabilities of the sensor nodes.

In addition, the sensors are in many cases battery-powered which limits the lifespan of such sensors unless energy harvesting recharge mechanism is included [30,31,32,33,34]. In such cases without battery recharge, the possible duration of the battery is dependent upon many factors. One, the battery much provide transmitter power which will be adequate to withstand the various propagation losses the wireless signal will

subjected to in its propagation environment [35,36, 37,38, 39,40, 41,42, 43,44,45,46,47,48,49,50,51,52,53,54,55]. The longer the transmission path the higher the transmitter power and the more the energy demand on the battery [56,57,58,59,60,61,62,63,64,65]. More so, satellite-sensor communication link is possible but requires much power for the signal to transverse the distance from the earth to the satellite.

Other factors that can affect the energy demand on the battery of sensor nodes are the duty cycle, cycle time, energy demand in the active state and in the sleep state of the node and other parameters associated with the battery and sensor node. Accordingly, in this paper, the evaluation of the energy demand and lifespan of battery-powered ZigBee IEEE 802.15.4 compliant sensor node for Internet of Things-based applications is presented. The energy consumption of the sensor node is modelled using a four-state model and the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node parameters are used for numerical examples [70,71].

2. Methodology

2.1 Determination of the Energy Demand Profile

The low-end IoT device (LeIoT device) considered in this study is a battery-powered sensor node (with block diagram shown in Figure 1) with four distinct energy demand modes or states (Figure 2), namely; the sensing or data capture/processing mode, the transmission mode, the reception mode and the sleep/wake-up mode. In the diagram in Figure 2, the sleep mode consist of the sleep and wake-up sub-modes whereas, the active mode consists of the sensing or data capture/processing sub-mode, the transmission sub-mode, and the reception sub-mode. One transition from the sleep mode to the active mode and back to the sleep mode constitutes a cycle and the LeIoT device goes through the cycle periodically for a number of cycles in a day.

The time spent by the LeIoT device in each of the modes are denoted respectively as ; T_M, T_T, T_R , and T_S where the time is in ms unless otherwise stated. The current drawn by the LeIoT device in each of the modes are denoted respectively as ; I_M, I_T, I_R and I_S , where the

current is in mA unless otherwise stated. Similarly, the energy consumed by the LeIoT device in each of the modes are denoted respectively as; E_M, E_T, E_R and E_S , where the energy is in mJ unless otherwise stated.

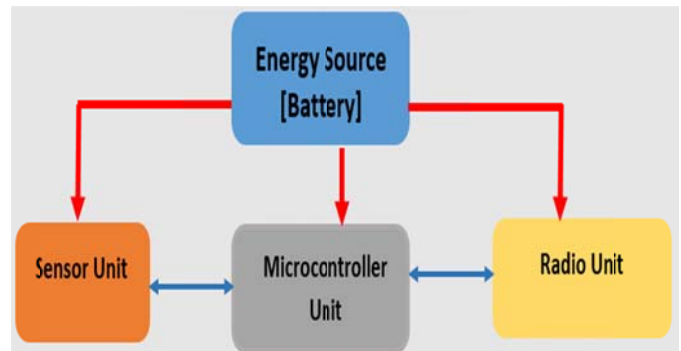


Figure 1 The block diagram of a typical battery-powered sensor node used as the case study low-end IoT device

The operating voltage (in volt) of the LeIoT device and battery is denoted as V_{op} . The LeIoT device is assumed operate in a periodic cycles that consist of data capture/processing operations, transmission of data, and reception of data or acknowledgment and enters the sleep mode for the remaining part of the time in the given cycle.

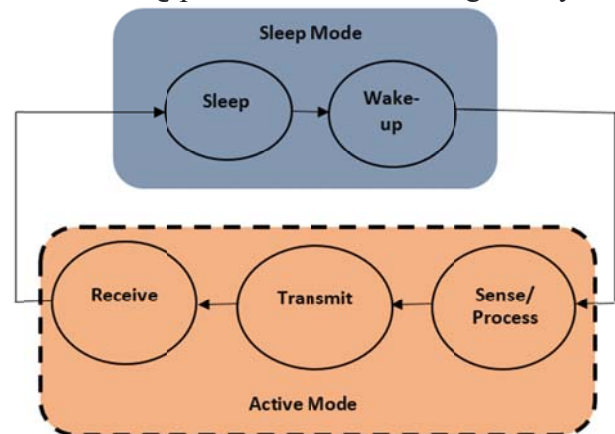


Figure 2 The diagram showing the low-end IoT device modes and state transition

The duration of one cycle is denoted as T_{CY} , and the number of cycles or data capture in a day is denoted as n_{CY} . Then, T_{CY} in ms is given as follows;

$$T_{msHR} = 60 * 60 * 1000 \quad (1)$$

$$T_{CY} = \left(\frac{24 (T_{msHR})}{n_{CY}} \right) \quad (2)$$

The data capture, transmission and reception modes are collectively referred as the active state of the LeIoT device with time, current and energy

denoted as T_A , I_A and E_A respectively. Then, the duty, D_{CY} in % and the energy demand, E_M, E_T, E_R and E_S given as follows;

$$T_A = T_M + T_T + T_R \quad (3)$$

$$T_S = T_{CY} - T_A = \left(\frac{24(T_{msHR})}{n_{CY}} \right) - T_A \quad (4)$$

$$D_{CY} = \left(\frac{T_A}{T_{CY}} \right) 100 \% \quad (5)$$

$$E_M = (I_M)(T_M) V_{op} \quad (6)$$

$$E_T = (I_T)(T_T) V_{op} \quad (7)$$

$$E_R = (I_R)(T_R) V_{op} \quad (8)$$

$$E_S = (I_S)(T_S) V_{op} \quad (9)$$

$$E_A = E_M + E_T + E_R \quad (10)$$

2.2 Determination of the battery-powered device lifespan

The LeIoT device is powered by a battery with rated capacity C_{BRC} in mAh and percentage of useful capacity, C_{BUP} , then the effective battery capacity, C_{BEC} in mAh and the LeIoT device lifespan in hours, T_{Lhr} are given as follows;

$$C_{BEC} = \frac{(C_{Bat})(C_{BUP})}{100} \quad (11)$$

$$I_{AV} = \frac{\{(T_T * I_T) + (T_R * I_R) + (T_M * I_M) + (T_S * I_S)\}}{T_M + T_T + T_R + T_S} \quad (12)$$

$$T_{Lhr} = \frac{C_{BEC}}{I_{AV}} \quad (13)$$

Furthermore, the LeIoT device lifespan in days, T_{Ld} and in years, T_{Ly} are given as follows;

$$T_{Ld} = \frac{24(C_{BEC})}{I_{AV}} \quad (14)$$

$$T_{Ly} = \frac{8760(C_{BEC})}{I_{AV}} \quad (15)$$

The energy consumption parameters of Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor

Table 2 The results for the power profile, as well as the energy consumed per cycle and per day in each of the four states of the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Sensor Node Mode	Current, I (mA)	Time, t (mS)	Power (W)	Energy (mJ) consumed per cycle	Energy (mJ) consumed per day
Transmit	17.4	865	0.04698	40.6377	8637.39
Receive	19.7	100	0.05319	5.319	1130.53
Measure	8	3100	0.0216	66.96	14232.09
Sleep	0.015	402435	0.0000405	16.2986	3464.21
Total				129.22	27464.21508

node (as presented in Table 1) is used in this study for the numerical examples.

Table 1 The energy consumption parameters of ZigBee IEEE 802.15.4 compliant sensor nodes used in this study [70,71]

S/N	Parameter	Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node
1	Data rate	250 kb
2	Sleep mode	15 μ A
3	Processor consumption	8 mA
4	Transmission	17.4 mA
5	Reception	19.7
6	Supply voltage	2.7

3 Results and discussion

The requisite impute parameters for the case study sensor node were used to compute the energy consumption, lifespan and other relevant parameters and the results are presented and discussed. The results for the power profile, as well as the energy consumed per cycle and per day in each of the four states of the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node are shown in Table 2. The results in Table 2 show that the data capture (measure) state has the highest energy consumption of 66.96 mJ per cycle followed by the transmit state with per cycle energy consumption of 40.6377 mJ, as shown in Figure 3.

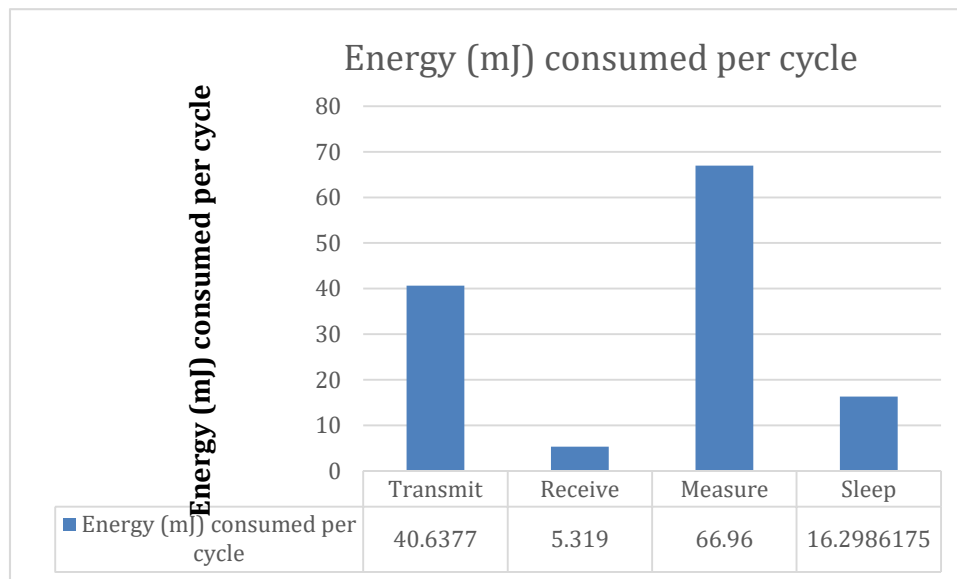


Figure 3. Per cycle energy consumption in each of the four states of the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

The active states time and current parameter values are maintained while the duty cycle is varied from 1 % to 30 %. The results on the impact of duty cycle on the cycle time and number of data capture for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node are shown in Table 3 and Figure 4. The results in Table 3 and Figure 4 show that increasing the duty cycle while maintaining the active state time duration amounts to reduction in the cycle time and increase in the number of cycles (or number of data capture) per day.

The results on the impact of duty cycle on the energy consumed per cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node are shown in Table 4 and Figure 5. The results in Table 4 and Figure 5 show that increasing the duty cycle while maintaining the active state time and current parameter values amounts to reduction in the sleep state time and cycle time and hence decrease in the energy consumed in the sleep time and energy consumed

per cycle. In this case, the energy consumed in the active state is constant.

The results on the impact of duty cycle on energy consumed per day for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node are shown in Table 5 and Figure 6. The results show that the resultant effect of the increase in the duty cycle is increase in the daily energy consumption. This seems to contradict the decrease in the per cycle energy consumption with increase in duty cycle. The increase in per day energy consumption is due to the rapid increase in the number of cycles per day.

The results on the impact of duty cycle on the battery lifespan and number of bits transmitted for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node are shown in Table 6, Figure 7 and Figure 8. The results in Figure 7 and Figure 8 show that while the battery lifespan decreases with increase in duty cycle the total number of bits transmitted over the battery lifespan increases with the duty cycle. This is due to the rapid increase in the number of cycles per day as the duty cycle increases.

Table 3 The results on the impact of duty cycle on the cycle time and number of data capture for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Duty Cycle (%)	Cycle Time (s)	Number of cycles per day	Duty Cycle (%)	Cycle Time (s)	Number of cycles per day
1	406.5	212.5461	16	25.40625	3400.738
2	203.25	425.0923	18	22.58333	3825.83
4	101.625	850.1845	20	20.325	4250.923
6	67.75	1275.277	22	18.47727	4676.015

8	50.8125	1700.369	24	16.9375	5101.107
10	40.65	2125.461	26	15.63462	5526.199
12	33.875	2550.554	28	14.51786	5951.292
14	29.03571	2975.646	30	13.55	6376.384

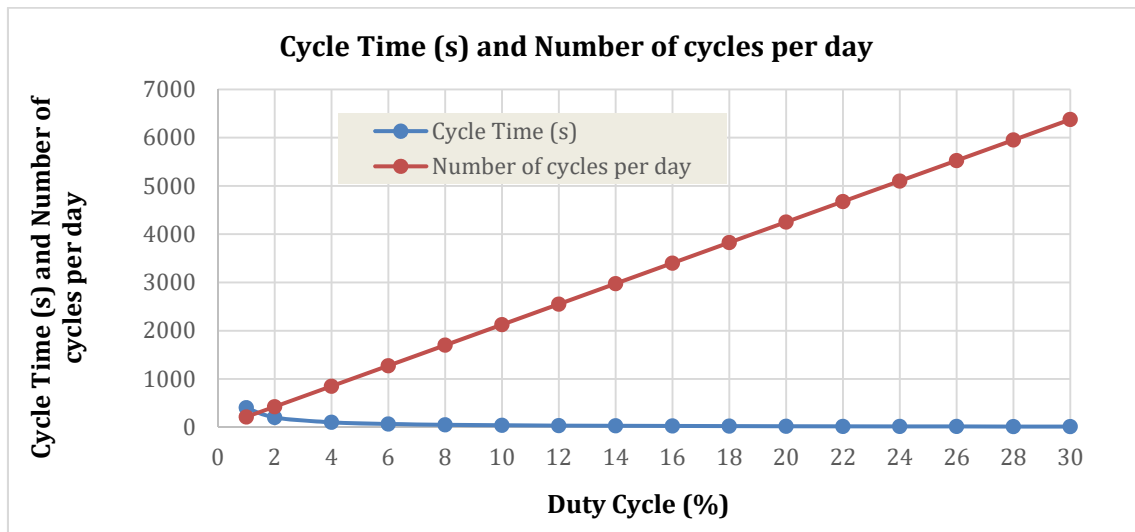


Figure 4 The graph of cycle time and number of data capture versus duty cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Table 4 The results on the impact of duty cycle on the energy consumed per cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Duty Cycle (%)	Eactv (mJ) per cycle	Eslp (mJ) per cycle	Eperiod (mJ) per cycle	Duty Cycle (%)	Eactv (mJ) per cycle	Eslp (mJ) per cycle	Eperiod (mJ) per cycle
1	112.9	16.3	129.2	16.0	112.9	0.9	113.8
2	112.9	8.1	121.0	18.0	112.9	0.7	113.7
4	112.9	4.0	116.9	20.0	112.9	0.7	113.6
6	112.9	2.6	115.5	22.0	112.9	0.6	113.5
8	112.9	1.9	114.8	24.0	112.9	0.5	113.4
10	112.9	1.5	114.4	26.0	112.9	0.5	113.4
12	112.9	1.2	114.1	28.0	112.9	0.4	113.3
14	112.9	1.0	113.9	30.0	112.9	0.4	113.3

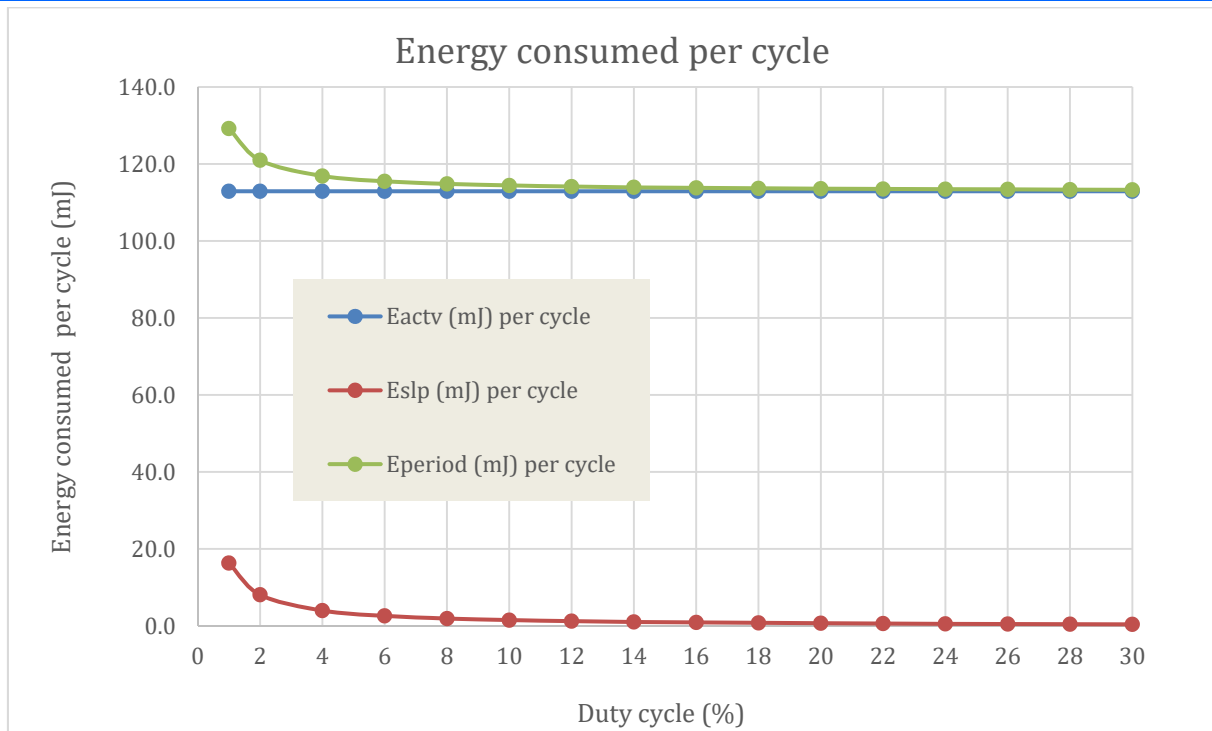


Figure 5 The graph of energy consumed per cycle versus duty cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Table 5 The results on the impact of duty cycle on energy consumed per day for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Duty Cycle (%)	Energy (mJ) consumed per day	Duty Cycle (%)	Energy (mJ) consumed per day
1	27464.2	16	386939.4
2	51429.2	18	434869.5
4	99359.3	20	482799.5
6	147289.3	22	530729.5
8	195219.3	24	578659.6
10	243149.4	26	626589.6
12	291079.4	28	674519.6
14	339009.4	30	722449.7

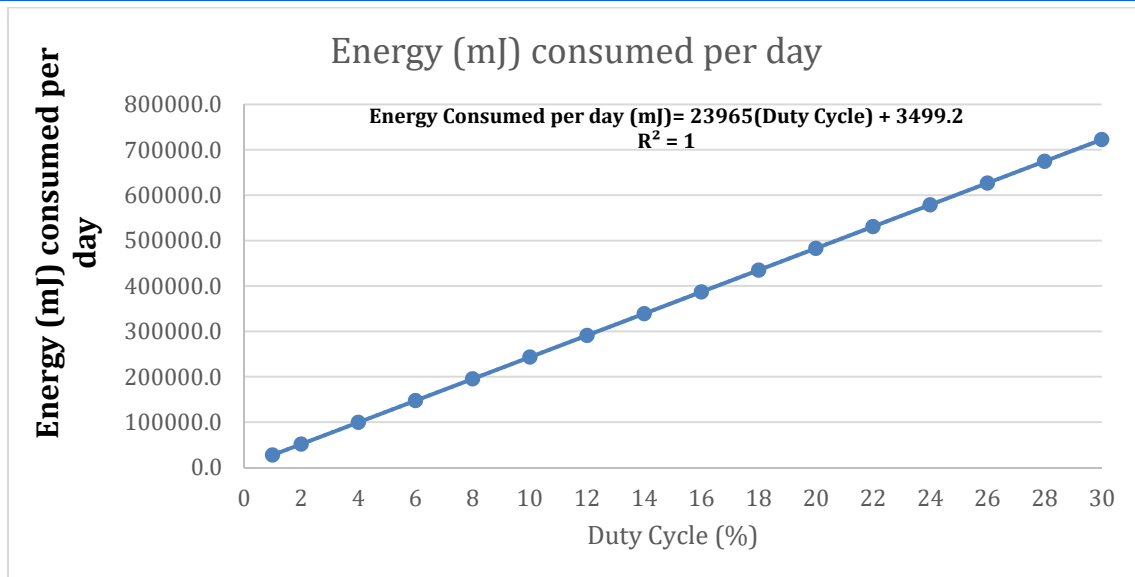


Figure 6 The graph of energy consumed per day versus duty cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Table 6 The results on the impact of duty cycle on the battery lifespan, number of bits transmitted and energy consumed for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

Duty Cycle (%)	Battery Lifespan (hour)	Number of cycles in battery lifespan	Number of bits transmitted in battery lifespan (bits)	Energy (mJ) consumed in battery lifespan	Duty Cycle (%)	Battery Lifespan (hour)	Number of cycles in battery lifespan	Number of bits transmitted in battery lifespan (bits)	Energy (mJ) consumed in battery lifespan
1	22,084	195,581	16,819,925	25,272,000	16	1,568	222,111	19,101,534	25,272,000
2	11,793	208,888	17,964,338	25,272,000	18	1,395	222,334	19,120,746	25,272,000
4	6,104	216,244	18,597,000	25,272,000	20	1,256	222,513	19,136,144	25,272,000
6	4,118	218,813	18,817,908	25,272,000	22	1,143	222,660	19,148,761	25,272,000
8	3,107	220,120	18,930,341	25,272,000	24	1,048	222,782	19,159,288	25,272,000
10	2,494	220,912	18,998,449	25,272,000	26	968	222,886	19,168,204	25,272,000
12	2,084	221,443	19,044,127	25,272,000	28	899	222,975	19,175,853	25,272,000
14	1,789	221,824	19,076,888	25,272,000	30	840	223,052	19,182,488	25,272,000

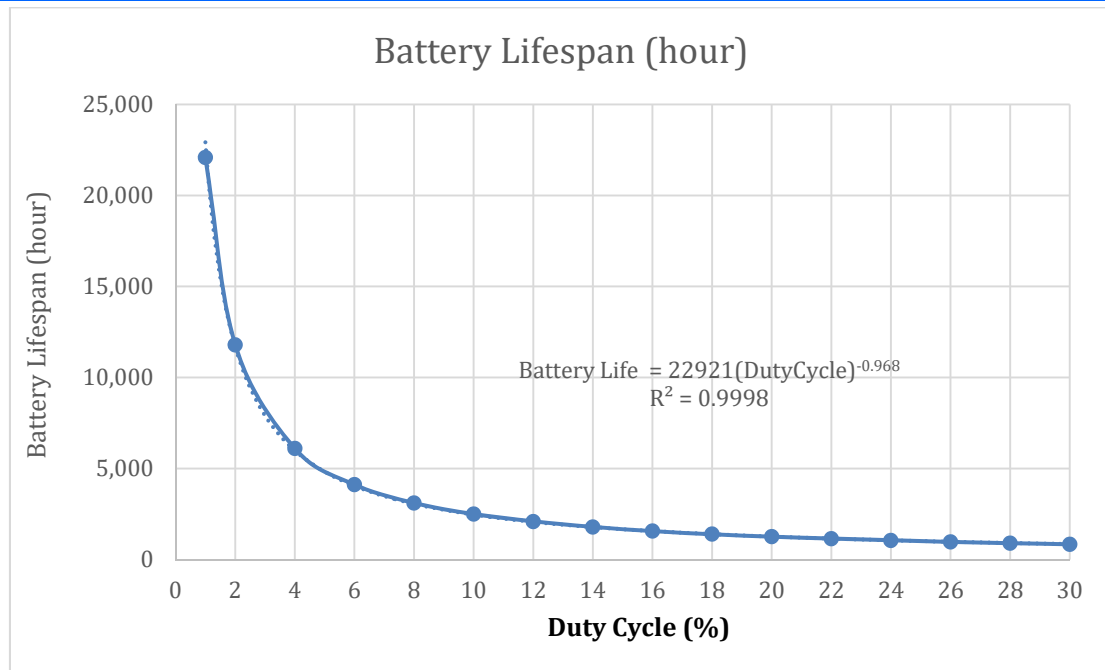


Figure 7 The graph of battery lifespan versus duty cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

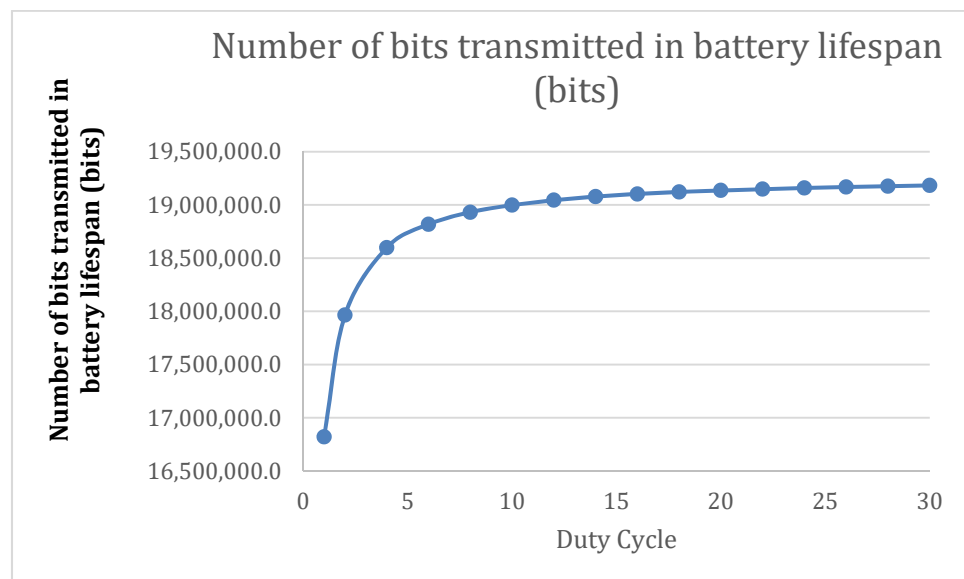


Figure 8 The graph of number of bits transmitted in battery lifespan versus duty cycle for the Crossbow MICAz ZigBee IEEE 802.15.4 compliant sensor node

4. Conclusion

The energy consumption and battery lifespan, as well as the impact of duty cycle on the energy consumption and data communication capability of a ZigBee IEEE802.15.4 compliant sensor node is presented. The sensor node energy consumption is modelled with four states and which it runs in each cycle with a given cycle time and duty cycle. The results show that if active states time and current parameter values

are maintained while the duty cycle is increased, the battery lifespan decreases but the number of bits transmitted over the battery lifespan increases. This is due to rapid increase in the number of cycles per day with increase in duty cycle is increased. Also, the energy consumption per day increases with increase in the duty cycle. In all, the specific impact of increase in the duty cycle on the energy consumption of the sensor node depends on which parameters are kept constant and which ones are varied.

References

1. Wu, L., Yue, X., Jin, A., & Yen, D. C. (2016). Smart supply chain management: a review and implications for future research. *The International Journal of Logistics Management*.
2. Bibri, S. E. (2019). On the sustainability of smart and smarter cities in the era of big data: an interdisciplinary and transdisciplinary literature review. *Journal of Big Data*, 6(1), 1-64.
3. Eremia, M., Toma, L., & Sanduleac, M. (2017). The smart city concept in the 21st century. *Procedia Engineering*, 181, 12-19.
4. Chernyshev, M., Baig, Z., Bello, O., & Zeadally, S. (2017). Internet of things (IoT): Research, simulators, and testbeds. *IEEE Internet of Things Journal*, 5(3), 1637-1647.
5. Bibri, S. E. (2018). *Smart sustainable cities of the future*. Springer Berlin Heidelberg.
6. Kim, K. J., & Shin, D. H. (2015). An acceptance model for smart watches: Implications for the adoption of future wearable technology. *Internet Research*.
7. Hammi, Badis, Rida Khatoun, Sherali Zeadally, Achraf Fayad, and Lyes Khoukhi. "IoT technologies<? show [AQ ID= Q1]?> for smart cities." *IET networks* 7, no. 1 (2018): 1-13.
8. Tao, F., Qi, Q., Wang, L., & Nee, A. Y. C. (2019). Digital twins and cyber-physical systems toward smart manufacturing and industry 4.0: Correlation and comparison. *Engineering*, 5(4), 653-661.
9. Jalali, R., El-Khatib, K., & McGregor, C. (2015, February). Smart city architecture for community level services through the internet of things. In *2015 18th International Conference on Intelligence in Next Generation Networks* (pp. 108-113). IEEE.
10. Samuel, Wali, Simeon Ozuomba, and Philip M. Asuquo (2019). EVALUATION OF WIRELESS SENSOR NETWORK CLUSTER HEAD SELECTION FOR DIFFERENT PROPAGATION ENVIRONMENTS BASED ON LEE PATH LOSS MODEL AND K-MEANS ALGORITHM. EVALUATION, 3(11). *Science and Technology Publishing (SCI & TECH) Vol. 3 Issue 11, November – 2019*
11. Faheem, M., & Gungor, V. C. (2018). Energy efficient and QoS-aware routing protocol for wireless sensor network-based smart grid applications in the context of industry 4.0. *Applied Soft Computing*, 68, 910-922.
12. Samuel, W., Ozuomba, Simeon, & Constance, K. (2019). SELF-ORGANIZING MAP (SOM) CLUSTERING OF 868 MHZ WIRELESS SENSOR NETWORK NODES BASED ON EGLI PATHLOSS MODEL COMPUTED RECEIVED SIGNAL STRENGTH. *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 6 Issue 12, December – 2019*
13. Al-Turjman, F., & Lemayian, J. P. (2020). Intelligence, security, and vehicular sensor networks in internet of things (IoT)-enabled smart-cities: An overview. *Computers & Electrical Engineering*, 87, 106776.
14. Njoku, Felix A., Ozuomba Simeon, and Fina Otosi Faithpraise (2019). Development Of Fuzzy Inference System (FIS) For Detection Of Outliers In Data Streams Of Wireless Sensor Networks. *International Multilingual Journal of Science and Technology (IMJST) Vol. 4 Issue 10, October – 2019*
15. Faheem, M., & Gungor, V. C. (2018). MGRP: Mobile sinks-based QoS-aware data gathering protocol for wireless sensor networks-based smart grid applications in the context of industry 4.0-based on internet of things. *Future Generation Computer Systems*, 82, 358-374.
16. Simeon, Ozuomba. (2020). "APPLICATION OF KMEANS CLUSTERING ALGORITHM FOR SELECTION OF RELAY NODES IN WIRELESS SENSOR NETWORK." *International Multilingual Journal of Science and Technology (IMJST) Vol. 5 Issue 6, June – 2020*
17. Sadeghi, A. R., Wachsmann, C., & Waidner, M. (2015, June). Security and privacy challenges in industrial internet of things. In *2015 52nd ACM/EDAC/IEEE Design Automation Conference (DAC)* (pp. 1-6). IEEE.
18. Simeon, Ozuomba. (2020). "Analysis Of Effective Transmission Range Based On Hata Model For Wireless Sensor Networks In The C-Band And Ku-Band." *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 7 Issue 12, December - 2020*
19. Thoben, K. D., Wiesner, S., & Wuest, T. (2017). "Industrie 4.0" and smart manufacturing-a review of research issues and application examples. *International journal of automation technology*, 11(1), 4-16.
20. Ali, A. S., Zanzinger, Z., Debose, D., & Stephens, B. (2016). Open Source Building Science Sensors (OSBSS): A low-cost Arduino-based platform for long-term indoor environmental data collection. *Building and Environment*, 100, 114-126.
21. Panda, M., & Khilar, P. M. (2015). Distributed self fault diagnosis algorithm for large scale wireless sensor networks using modified three sigma edit test. *Ad Hoc Networks*, 25, 170-184.
22. Ransing, R. S., & Rajput, M. (2015, January). Smart home for elderly care, based on Wireless Sensor Network. In *2015 International Conference on Nascent Technologies in the Engineering Field (ICNTE)* (pp. 1-5). IEEE.

23. Cai, Y., Starly, B., Cohen, P., & Lee, Y. S. (2017). Sensor data and information fusion to construct digital-twins virtual machine tools for cyber-physical manufacturing. *Procedia manufacturing*, 10, 1031-1042.
24. Parkinson, T., Parkinson, A., & de Dear, R. (2019). Continuous IEQ monitoring system: Context and development. *Building and Environment*, 149, 15-25.
25. Zhang, Y., Yang, W., Han, D., & Kim, Y. I. (2014). An integrated environment monitoring system for underground coal mines—Wireless sensor network subsystem with multi-parameter monitoring. *Sensors*, 14(7), 13149-13170.
26. Alvear, O., Calafate, C. T., Cano, J. C., & Manzoni, P. (2018). Crowdsensing in smart cities: Overview, platforms, and environment sensing issues. *Sensors*, 18(2), 460.
27. Clements, A. L., Griswold, W. G., Rs, A., Johnston, J. E., Herting, M. M., Thorson, J., ... & Hannigan, M. (2017). Low-cost air quality monitoring tools: from research to practice (a workshop summary). *Sensors*, 17(11), 2478.
28. Kos, A., Tomažič, S., & Umek, A. (2016). Evaluation of smartphone inertial sensor performance for cross-platform mobile applications. *Sensors*, 16(4), 477.
29. Olsson, R. H., Bogoslovov, R. B., & Gordon, C. (2016, October). Event driven persistent sensing: Overcoming the energy and lifetime limitations in unattended wireless sensors. In *2016 IEEE SENSORS* (pp. 1-3). IEEE.
30. La Rosa, R., Zoppi, G., Di Donato, L., Sorbello, G., Di Carlo, C. A., & Livreri, P. (2018, September). A battery-free smart sensor powered with rf energy. In *2018 IEEE 4th International Forum on Research and Technology for Society and Industry (RTSI)* (pp. 1-4). IEEE.
31. Engmann, F., Katsriku, F. A., Abdulai, J. D., Adu-Manu, K. S., & Banaseka, F. K. (2018). Prolonging the lifetime of wireless sensor networks: a review of current techniques. *Wireless Communications and Mobile Computing*, 2018.
32. Jeon, K. E., She, J., Xue, J., Kim, S. H., & Park, S. (2019). luXbeacon—A batteryless beacon for green IoT: Design, modeling, and field tests. *IEEE Internet of Things Journal*, 6(3), 5001-5012.
33. Xia, C., Liu, W., & Deng, Q. (2015). Cost minimization of wireless sensor networks with unlimited-lifetime energy for monitoring oil pipelines. *IEEE/CAA Journal of Automatica Sinica*, 2(3), 290-295.
34. bin Baharudin, A. M., Saari, M., Sillberg, P., Rantanen, P., Soini, J., & Kuroda, T. (2016, October). Low-energy algorithm for self-controlled Wireless Sensor Nodes. In *2016 International Conference on Wireless Networks and Mobile Communications (WINCOM)* (pp. 42-46). IEEE.
35. Simeon, Ozuomba. (2016) "Comparative Analysis Of Rain Attenuation In Satellite Communication Link For Different Polarization Options." *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 3 Issue 6, June – 2016*
36. Liaskos, C., Nie, S., Tsioliariidou, A., Pitsillides, A., Ioannidis, S., & Akyildiz, I. (2018). A new wireless communication paradigm through software-controlled metasurfaces. *IEEE Communications Magazine*, 56(9), 162-169.
37. Cui, W., Shen, K., & Yu, W. (2019). Spatial deep learning for wireless scheduling. *IEEE journal on selected areas in communications*, 37(6), 1248-1261.
38. Simeon, Ozuomba. (2017). "Determination Of The Clear Sky Composite Carrier To Noise Ratio For Ku-Band Digital Video Satellite Link" *Science and Technology Publishing (SCI & TECH) Vol. 1 Issue 7, July – 2017*
39. Zhang, Y., Wen, J., Yang, G., He, Z., & Luo, X. (2018). Air-to-air path loss prediction based on machine learning methods in urban environments. *Wireless Communications and Mobile Computing*, 2018.
40. Imoh-Etefia, Ubon Etefia, Ozuomba Simeon, and Stephen Bliss Utibe-Abasi. (2020). "Analysis Of Obstruction Shadowing In Bullington Double Knife Edge Diffraction Loss Computation." *Journal of Multidisciplinary Engineering Science Studies (JMESS) Vol. 6 Issue 1, January – 2020*
41. Haneda, K., Järveläinen, J., Karttunen, A., Kyrö, M., & Putkonen, J. (2015). A statistical spatio-temporal radio channel model for large indoor environments at 60 and 70 GHz. *IEEE Transactions on Antennas and Propagation*, 63(6), 2694-2704.
42. Simeon, Ozuomba, Ezuruike Okafor SF, and Bankole Morakinyo Olumide (2018). Development of Mathematical Models and Algorithms for Exact Radius of Curvature Used in Rounded Edge Diffraction Loss Computation. Development, 5(12). *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 5 Issue 12, December – 2018*
43. Dialoke, Ikenna Calistus, Ozuomba Simeon, and Henry Akpan Jacob. (2020) "ANALYSIS OF SINGLE KNIFE EDGE DIFFRACTION LOSS FOR A FIXED TERRESTRIAL LINE-OF-SIGHT MICROWAVE COMMUNICATION LINK." *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 7 Issue 2, February - 2020*
44. Akaninyene B. Obot , Ozuomba Simeon and Afolanya J. Jimoh (2011); "Comparative Analysis Of Pathloss Prediction Models For Urban Macrocellular" *Nigerian Journal of Technology (NIJOTECH) Vol. 30, No. 3 , October 2011 , PP 50 – 59*

45. Chen, J., Ge, X., & Ni, Q. (2019). Coverage and handoff analysis of 5G fractal small cell networks. *IEEE Transactions on Wireless Communications*, 18(2), 1263-1276.
46. Akaninyene B. Obot , Ozuomba Simeon and Kingsley M. Udofia (2011); "Determination Of Mobile Radio Link Parameters Using The Path Loss Models" *NSE Technical Transactions , A Technical Journal of The Nigerian Society Of Engineers*, Vol. 46, No. 2 , April - June 2011 , PP 56 – 66.
47. Njoku Chukwudi Aloziem, Ozuomba Simeon, Afolayan J. Jimoh (2017) Tuning and Cross Validation of Blomquist-Ladell Model for Pathloss Prediction in the GSM 900 Mhz Frequency Band , *International Journal of Theoretical and Applied Mathematics*
48. Ozuomba, Simeon, Johnson, E. H., & Udoiwod, E. N. (2018). Application of Weissberger Model for Characterizing the Propagation Loss in a *Gliricidia sepium* Arboretum. *Universal Journal of Communications and Network*, 6(2), 18-23.
49. Afaqui, M. S., Garcia-Villegas, E., Lopez-Aguilera, E., Smith, G., & Camps, D. (2015, March). Evaluation of dynamic sensitivity control algorithm for IEEE 802.11 ax. In *2015 IEEE wireless communications and networking conference (WCNC)* (pp. 1060-1065). IEEE.
50. Constance, Kalu, Ozuomba Simeon, and Ezuruike Okafor SF. (2018). Evaluation of the Effect of Atmospheric Parameters on Radio Pathloss in Cellular Mobile Communication System. Evaluation, 5(11). *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 5 Issue 11, November - 2018*
51. Sun, S., Rappaport, T. S., Thomas, T. A., Ghosh, A., Nguyen, H. C., Kovács, I. Z., ... & Partyka, A. (2016). Investigation of prediction accuracy, sensitivity, and parameter stability of large-scale propagation path loss models for 5G wireless communications. *IEEE transactions on vehicular technology*, 65(5), 2843-2860.
52. Hussain, S. (2017). *Efficient ray-tracing algorithms for radio wave propagation in urban environments* (Doctoral dissertation, Dublin City University).
53. Kalu Constance, Ozuomba Simeon, Umana, Sylvester Isreal (2018). Evaluation of Walficsh-Bertoni Path Loss Model Tuning Methods for a Cellular Network in a Timber Market in Uyo. *Journal of Multidisciplinary Engineering Science Studies (JMESS) Vol. 4 Issue 12, December - 2018*
54. Thotahewa, K. M., Redoutè, J. M., & Yuce, M. R. (2015). Propagation, power absorption, and temperature analysis of UWB wireless capsule endoscopy devices operating in the human body. *IEEE Transactions on Microwave Theory and Techniques*, 63(11), 3823-3833.
55. Ma, J., Shrestha, R., Adelberg, J., Yeh, C. Y., Hossain, Z., Knightly, E., ... & Mittleman, D. M. (2018). Security and eavesdropping in terahertz wireless links. *Nature*, 563(7729), 89-93.
56. Ozuomba Simeon (2019) Evaluation Of Optimal Transmission Range Of Wireless Signal On Different Terrains Based On Ericsson Path Loss Model Vol. 3 Issue 12, December - 2019 Available at : <http://www.scitechpub.org/wp-content/uploads/2021/03/SCITECHP420157.pdf>
57. Narzisi, G., O'rawe, J. A., lossifov, I., Fang, H., Lee, Y. H., Wang, Z., ... & Schatz, M. C. (2014). Accurate de novo and transmitted indel detection in exome-capture data using microassembly. *Nature methods*, 11(10), 1033-1036.
58. Bor, M. C., Roedig, U., Voigt, T., & Alonso, J. M. (2016, November). Do LoRa low-power wide-area networks scale?. In *Proceedings of the 19th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems* (pp. 59-67).
59. Kalu, C., Ozuomba, Simeon. & Udofia, K. (2015). Web-based map mashup application for participatory wireless network signal strength mapping and customer support services. *European Journal of Engineering and Technology*, 3 (8), 30-43.
60. Jiang, D., Ying, X., Han, Y., & Lv, Z. (2016). Collaborative multi-hop routing in cognitive wireless networks. *Wireless personal communications*, 86(2), 901-923.
61. Mao, Y., Zhang, J., & Letaief, K. B. (2017, March). Joint task offloading scheduling and transmit power allocation for mobile-edge computing systems. In *2017 IEEE wireless communications and networking conference (WCNC)* (pp. 1-6). IEEE.
62. Van der Bergh, B., Chiumento, A., & Pollin, S. (2016). LTE in the sky: Trading off propagation benefits with interference costs for aerial nodes. *IEEE Communications Magazine*, 54(5), 44-50.
63. Johnson, Enyenihi Henry, Simeon Ozuomba, and Ifiok Okon Asuquo. (2019). Determination of Wireless Communication Links Optimal Transmission Range Using Improved Bisection Algorithm. *Universal Journal of Communications and Network*, 7(1), 9-20.

64. Wu, Q., & Zhang, R. (2019). Intelligent reflecting surface enhanced wireless network via joint active and passive beamforming. *IEEE Transactions on Wireless Communications*, 18(11), 5394-5409.
65. Sadowski, S., & Spachos, P. (2018). Rssi-based indoor localization with the internet of things. *IEEE Access*, 6, 30149-30161.
66. Liu, J., Shi, Y., Fadlullah, Z. M., & Kato, N. (2018). Space-air-ground integrated network: A survey. *IEEE Communications Surveys & Tutorials*, 20(4), 2714-2741.
67. Amanor, D. N. (2017). *Visible light communication physical layer development for inter-satellite communication* (Doctoral dissertation, North Carolina Agricultural and Technical State University).
68. Helder, D., Markham, B., Morfitt, R., Storey, J., Barsi, J., Gascon, F., ... & Pahlevan, N. (2018). Observations and recommendations for the calibration of Landsat 8 OLI and Sentinel 2 MSI for improved data interoperability. *Remote Sensing*, 10(9), 1340.
69. Jiang, S., Portillo-Quintero, C., Sanchez-Azofeifa, A., & MacGregor, M. H. (2014, September). Predicting RF path loss in forests using satellite measurements of vegetation indices. In *39th Annual IEEE Conference on Local Computer Networks Workshops* (pp. 592-596). IEEE.
70. Simeon, Ozuomba (2014) "Fixed Point Iteration Computation Of Nominal Mean Motion And Semi Major Axis Of Artificial Satellite Orbiting An Oblate Earth." *Journal of Multidisciplinary Engineering Science and Technology (JMEST) Vol. 1 Issue 4, November – 2014*
71. Crossbow MICAz IEEE 802.15.4/Zigbee and Waspote 802.15.4/Zigbee
72. Zungeru, A. M., Ang, L. M., Prabaharan, S. R. S., & Seng, K. P. (2012). Radio frequency energy harvesting and management for wireless sensor networks. *Green mobile devices and networks: Energy optimization and scavenging techniques*, (13), 341-368.