Nigerian Journal of Technology (NIJOTECH)
Vol. 43, No. 3, September, 2024, pp.549 - 556
www.nijotech.com

Print ISSN: 0331-8443
Electronic ISSN: 2467-8821
https://doi.org/10.4314/njt.v43i3.18

ENERGY EFFICIENCY ANALYSIS OF EDGE IOT UMUDIGI A9 PRO ON CROSS-TIER NETWORKS: IMPACT OF DISTANCE AND USER-FRIENDLY APPLICATIONS

AUTHORS:
E. B. Mfonobong[1,*], C. Nkwachukwu[2], and L. S. Ezema[3]

AFFILIATIONS:
[1,2,3]Department of Electrical and Electronic Engineering, Federal University of Technology, Owerri, Imo State, Nigeria

***CORRESPONDING AUTHOR:**
Email: benson.mfonobong@futo.edu.ng

ARTICLE HISTORY:
Received: 05 January, 2024.
Revised: 10 May, 2024.
Accepted: 18 June, 2024.
Published: 20 September, 2024.

KEYWORDS:
Edge IoT, 3G and 4G network, Energy utilization, Distance impact, User-friendly applications, Mobile device efficiency.

ARTICLE INCLUDES:
Peer review

DATA AVAILABILITY:
On request from author(s)

EDITORS:
Chidozie Charles Nnaji

FUNDING:
None

Abstract
This paper investigated the energy utilisation of edge IoT mobile devices on the 3G and 4G networks, specifically focusing on the impact of the distance from the base station and user-friendly applications. Measurements were taken, and data was collected on a live network during active and passive sessions using enabling software on the test device. The study found that energy consumption varies based on distance, service type, and network usage. With IoT-matched software applications, the Umudigi A9 Pro device showed increased power consumption as distance from the base station increased and as a function of the network utilised. The study also examined video streaming, voice calls, and video playback services, focusing on their energy profiles. The analysis of both real-time and non-real-time services was carried out. Real-time services exhibited an average maximum power consumption of 243.2mW, while non-real-time usage averaged 209.1mW. The internal energy utilisation levels ranged from 370.1mW to 446.9mW for online idle radio operations and from 322.5mW to 458.3mW for offline idle radio operations, varying from the cell centre to the cell edge within a base station sector. It was shown that real-time applications on edge mobile user equipment (UEs) are more energy-intensive than other applications. Their energy requirements increased as these nodes moved towards the cell edge of the network coverage area, possibly due to Signal-to-Interference-plus-Noise Ratio (SINR) limitations. Real-time services require more energy than non-real-time services and understanding the relationship between signal strength and test device energy requirements about the service deployed can serve as an advisory tool for energy management.

HOW TO CITE:
Mfonobong, E. B., Nkwachukwu, C., and Ezema, L. S. "Energy Efficiency Analysis of Edge IoT Umudigi A9 Pro on Cross-Tier Networks: Impact of Distance and User-Friendly Applications", *Nigerian Journal of Technology*, 2024; 43(3), pp. 549 – 556; *https://doi.org/10.4314/njt.v43i3.18*

1.0 INTRODUCTION
Mobile devices and their applications have become part of our daily routine, even as we seek to improve efficiency [1-2]. The significant concern currently faced by users of these devices is power management [3-5]. As we know, these devices come with limited energy sources [6-8, 4], such that manufacturers provide them, and are currently made even more challenging to access and replace, hence the need for efficient utilisation. Several users complain of energy inefficiency without understanding the impact of location in the cell coverage area or primarily deployed applications [9], as they cannot understand the relationship between application types and user location on the network. Also, users need to determine energy-efficient applications [10] while limiting otherwise.

Researchers [11-15] have studied smart device energy utilisation based on network services like WiFi and

GSM, mobile device usage patterns, and energy usage at different states (on and off). Also, [17-19] investigated video service energy usage, focusing on quality delivery without specifying the network under investigation. From [16-19], the relationship between network quality and energy utilisation of smart mobile devices is crucial for users to understand and comprehend its impact on their device's performance. The knowledge so far could be more extensive and specific. Understanding the energy requirements of different applications, services, and device configurations is required to understand better energy utilisation on a broad scale, which should lead us to model efficiency. In this paper, an investigation of energy utilisation based on services deployed and network-specific applications to be achieved is to be presented.

The limited power source of mobile devices and their current high energy requirements have caused these devices to be perceived as inefficient by their users. This inefficiency has stirred up the need to investigate energy utilisation in multiple dimensions. It has been established that the energy utilisation of mobile devices is centred around its software and hardware subsystems [20, 21]. Different researchers have made efforts to investigate the energy utilisation of wireless mobile devices, such as [22], who investigated energy utilisation of wireless devices over different technologies such as WiFi and the 3G network to ascertain the best option. Also, [23] comparatively analysed the energy utilisation of wireless mobile devices and other dedicated devices with specific functions; this is made to understand the overall energy utilisation. [24] investigated the energy efficiency in multiple scenarios, including device-to-device (D2D) and device-to-network infrastructure over a simulated 5G network.

Furthermore, the reconfiguration of transport layers, such as user datagram protocol (UDP) and transmission control protocol (TCP), was investigated for energy-efficient utilisation [25]. In [26], the energy utilisation of some smartphones was investigated over multiple services such as WiFi, GPS, 3G networks, video playback, etc. The investigation was to give an overview of the energy profile of products based on the manufacturer's distinction. In [27], a battery consumption monitoring architecture was introduced to monitor utilisation levels, while in [28, 29], a model was designed to be capable of predicting the energy requirements of different tasks to make offloading decisions. In [30], air interface timeouts were identified and investigated for the best timeout values for specific carrier or user traffic profiles.

[31] Developed an energy consumption estimation technique capable of modelling the energy consumption according to various combinations of devices without additional hardware. Cognitive radio has been applied by [32] to manage energy based on QoS, channel conditions, and radio capabilities. A power amplifier and system power adaptation model were developed to adapt to the quality of service requirements. An approach such as machine learning and data mining was deployed in [33] using real-time experimental data collected. As seen in this paper, application-based energy utilisation investigations carried out as in [34] gave less information than desired because different devices handle power issues differently.

Previous researchers should have considered network quality variations, software internal energy utilisation, real-time and non-real-time application requirements, and the network on which these services are operated. It is crucial to identify software- and hardware-based energy requirements, understand variations based on device choice, and provide a valuable key performance indicator (KPI) for adaptive algorithms.

2.0 METHODOLOGY

The Umidigi A9 Pro with the following specifications: An octa-core processor (793 MHz–1807 MHz), 6 GB of RAM, and 128 GB of ROM, with up to 4G network capability, was used in this investigation. Two other mobile devices were deployed alongside to facilitate voice and video transmission, creating a closed network that aided data capture. The investigation was done on 3G and 4G networks deployed on 1100MHz and 2100MHz frequencies, respectively. Network coverage mapping was carried out while recording the received signal strength and quality, as the cell edge was identified as the point shortly before handover was initiated. The Umidigi A9 Pro was used as the test device, and we used software such as AccuBattery/Battery Guru, InWare, Battery Gauge, Google Map, and NetWard/NetMonster for battery life and utilisation monitoring, network identification and parameter tracking, handover indication, cell tracking, location, and distance measurement, respectively.

2.1 Analysis of Measured UE Power Utilisation

Power utilisation and sensing were measured for uplink and downlink for cell mapping and tracking purposes and UE power utilisation. The downlink RSRP measurement carried out enabled cell mapping, which led to cell edge identification and point of handover. This also guided the tracker to remain within a fixed network target.

https://doi.org/10.4314/njt.v43i3.18

a. Measured Downlink Channel Signal Characteristics

The Umidigi A9 Pro test device measured received power from a base station based on line-of-sight; we avoided obstruction, and distance from high-rise buildings was considered to prevent reflection signals. Google Maps and NetWard/NetMonster applications were used to measure distance, and we collected data from serving base stations for tracking and handover notifications. The NetMonster application identifies base stations and transfers location data to Google Maps for distance measurement.

Examining uplink and downlink characteristics is essential, as some assumptions will be drawn from both ends. This is because both links can be technically assumed to suffer from the same challenges, such as channel fading. The noise power is also considered the same across the uplink and downlink.

It is given that

$$RSSI = S + I + N \text{ (dBm)} \quad (1)$$

Where, RSSI is the received signal strength indicator, S is serving cell power, and I is the interference power. For wideband, N = full bandwidth, with up to 100 resource blocks per 20 MHz bandwidth. Therefore, RSSI will also be given as;

$$RSSI = 12 * N * RSRP\ (mW) \quad (2)$$

Where; Reference Signal Received Quality (RSRQ) quantifies the quality of the signal received with consideration of the noise and interference levels within the signal (in dB), and Reference Signal Received Power (RSRP) is the LTE power received over the provided bandwidth (in dBm). The quality of a channel can be evaluated based on the ratio between the received signal and interference with noise, as given;

$$RSRQ = \frac{RSRP}{RSSI/N} \quad (3)$$

RSSI is measured over 12 resource elements, making one resource block and one subframe for every signal burst. RSRP ranges from -75 to -120 dBm at the cell edge (RSRP mapping). N is physical resource blocks, RSRQ is defined from -3 dB to -19.5 dB, Noise power for 15 kHz = -125.2 dBm, Noise figure = 7 dBm, Temperature = 290K.

Assumption: RSRP does not contain noise power. Therefore, signal to noise ratio is given as;

$$SNR = \frac{RSRP}{P_{n-RE}} \quad (4)$$

Where, P_{n-RE} is the noise power per resource element;

Using Equation 5, noise power for 20 MHz as provided for by the LTE service provider whose power signal is analyzed will be -100.97 dBm; added UE noise figure of 7 dBm, we have -94 dBm. Therefore, noise power (P_n) is given as;

$$P_n = 10 \log_{10}\left(\frac{KBT}{1mW}\right) \quad (5)$$

Where, T is temperature (using 290k), B is Bandwidth in Hz, K is Boltzmann's constant, 1.38 x $10^{-23} m^2 kg K^{-1} s^{-2}$

b. Measured Uplink UE Power Utilisation Analysis:

The average power levels utilised for various services were measured and analysed, showing varying idle power consumption by user equipment (UE). The instability will likely be due to random or sequential pinging in the network as IoT-based devices exchange network state information and control power utilisation. Offline services track internal power consumption, and the device's screen is kept at maximum brightness to avoid artificial variations.

i. Voice call:

A voice call was initiated at several locations across the network, during which readings were taken. The power utilised was recorded over 5 seconds and averaged. This procedure was repeated for all the distances selected, as the test equipment was kept offline.

ii. Video call:

The test device was kept online during this session, and a video call was initiated. The energy expended was measured, recorded, and averaged over 5 seconds at every chosen location away from the base station.

iii. Video stream:

The video stream was done while the device was online. One of the streaming applications was deployed, and power expended was recorded over 5 seconds and averaged.

iv. Offline and Online Idle modes:

The test device was kept offline, and the utilised power was measured over 5 seconds and averaged. The same step was taken for the online idle mode. The test device was allowed to stay online without any active applications (this was achieved by blocking all applications from online activities). The energy expended was recorded and averaged over 5 seconds. Since video playback deploys different codecs with dissimilar energy requirements (Roman and Dmitriy, 2021), in this case, YouTube and MX video players in data compression, it was wise to note the duo. Offline media playback on YouTube using AV1 codec = 634 mW. Offline media playback using H264 codec = 645.4 mW.

It was impossible to accurately obtain the power expended during online transmission for network access, so it became imperative to use the difference between idle power and measured power during transmission on the three types of service under consideration to obtain the power expended during active mobile device usage. Using Equation (6 – 8), it is now possible to narrow down the focus on the energy expended during active device usage offline and online, respectively, as shown in Table 1.

The difference between the power utilised during the idle state of the test device and the measured power during the voice call session gives us the near actual power used for the service, as shown in Equation 6.

$$Voice\_Call_{offline} = Voice\_call \;-\; Idle_{offline} \qquad (6)$$

The measured power utilised on a video call while the device is online comprises the online idle state power, offline video playback power, and active video call power. Therefore, it was necessary to subtract the online idle power and offline video playback power from the measured power during the online video call session, as given in Equation 7.

$$Video\_call_{online} = V\_C_{online} - \left(I_{online} + V_{offline}\right) \quad (7)$$

Where, I_{online} is the energy utilised during the idle online state, and $V_{offline}$ is the energy used on video playback during the offline state.

The measured power utilised during the video stream session is believed to include the power used during the offline video playback. Therefore, subtracting the offline video playback power from the measured online video stream, as given in Equation 8, will narrow it down to near-actual power explicitly utilised for video streaming during the session.

$$Video\_stream_{online} = V\_S_{online} - V_{offline} \quad (8)$$

Where, V_S_{online} is the energy utilised during the online video stream.

The evaluated utilised power for all the services under consideration is presented in Table 1. Based on the evaluated data, the power utilisation of mobile equipment is higher for the hardware components of the test device.

Table 1: Service-based Measured UE Power

S/No	Distance (m)	Voice RT (dBm)	Video RT (dBm)	Video nRT (dBm)
1	35	9.73	19.86	16.39
2	85	7.78	13.54	16.87
3	180	11.81	19.63	16.36
4	360	17.72	21.95	20.46
5	515	18.50	22.49	22.35
6	645	20.95	23.85	23.20

Where; *Voice_RT* is the power utilised during an offline voice call operation, V_C_{online} is the power used during an online video call operation, V_S_{online} is the power used during an online video stream, $Idle_{online}$ is the power utilised while the device was online but not in active use, $Idle_{offline}$ is the power utilised while the device was offline and not actively in use.

The power dissipated on radio services (online) showed evidence of dependence on path loss and interference. It can be seen from the data presented that the energy dissipated during online service increased with an increase in distance from the serving base station. During the voice call application, we recorded a minimum power of 7.78dBm and a maximum power of 20.95dBm, a minimum of 19.86dBm, and a maximum of 23.85dBm were expended during a video call. In contrast, a minimum of 16.39dBm and a maximum of 23.20dBm were recorded as expended power during a video streaming session.

3.0 RESULTS AND DISCUSSION

The data collected during the field survey and the results obtained will be analysed as presented and discussed afterwards.

3.1 Results

a. eNB Power measurements

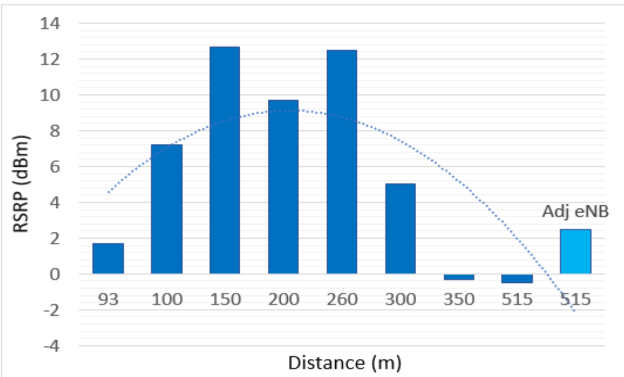

Figure 1: Measured macro-cell RSRP

The base station (eNB) signal strength was measured along a sector to identify the cell edge, avoiding trees, high-rise buildings and power lines. The results complied with the power decay constant given in theories, showing signal strength decay as expected. The received power quality was evaluated using the measured signal strength as given in Figure 1.

https://doi.org/10.4314/njt.v43i3.18

The signal-to-noise ratio (SNR) was recorded while SINR was evaluated from available data as given in Figure 2.

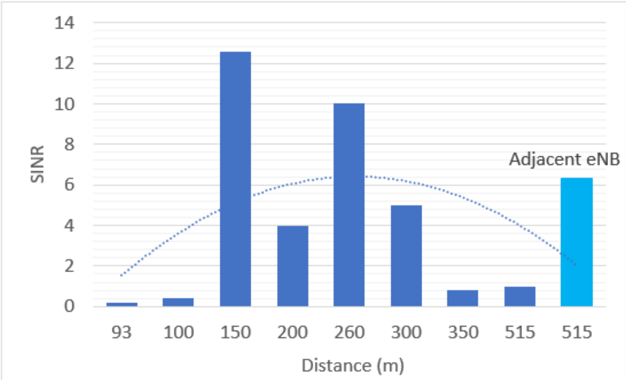

Figure 2: Measured macro-cell SINR

b. UE Hardware Power Utilisation Analysis

The UE screen and processors, as part of the hardware subsystem, were found to be critical components in high energy dissipation. To avoid complexity, a constant brightness level was applied. The impact of processors and GPU on energy utilisation was investigated, as shown in Figure 3.

i. UE Processor Activity

The study categorised services as RT and nRT, revealing that RT-video and RT-voice-only engage processors at higher frequencies, potentially causing higher power utilisation. At the same time, video streams pose threats to path loss. Figure 3 shows notable processor activities during the idle mode at the cell centre (idle C) and the cell edge (idle E).

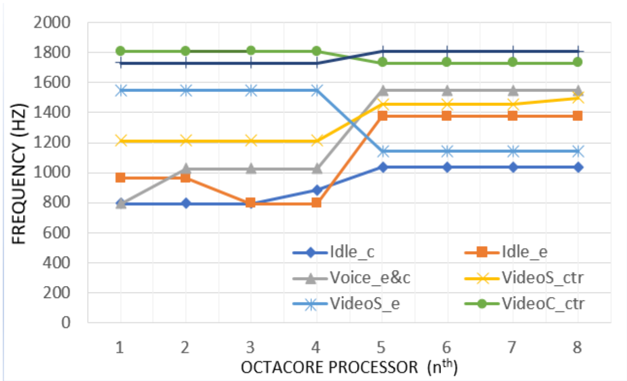

Figure 3: Measured processor clock-rate

The energy utilised during the survey was recorded for the four (4) scenarios as presented in Figure 4. Offline idle, online idle, video streaming (online), video playback (offline), voice call(offline) were the scenarios that were investigated.

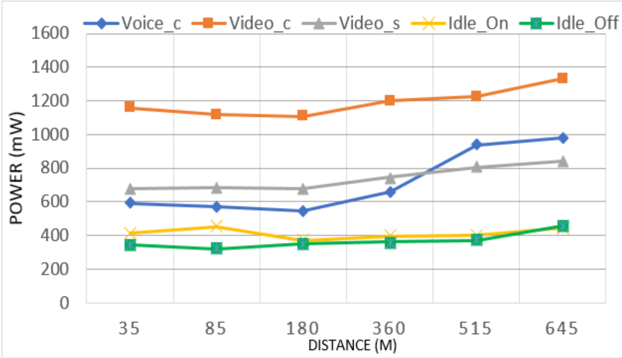

Figure 4: UE Power levels per deployed application

ii. UE Power Utilisation Based on Hardware and Network Variations

The study assessed user equipment's (UE) power consumption over 3G and 4G network technologies during mobile IoT scenarios as presented in Figures 5 and 6. Figure 5 shows power utilisation using 3G and 4G networks on an octa-core processor-enabled mobile device. Figure 6 shows values for similar network technology but a quad-core processor-powered mobile device.

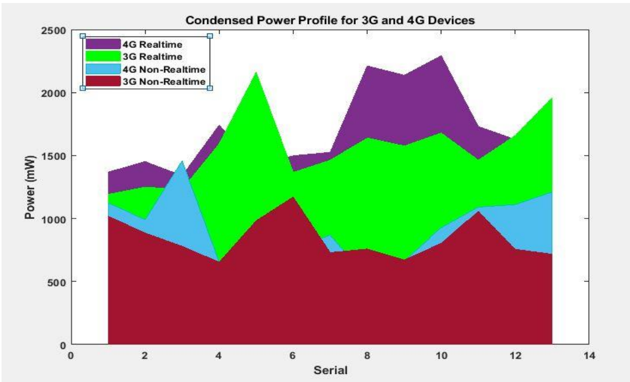

Figure 5: Power profile on o-core processor-enabled device

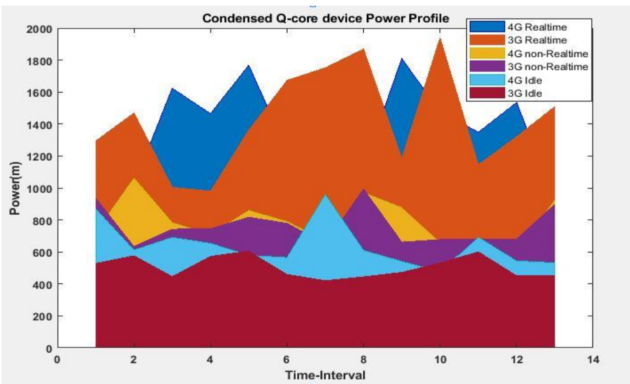

Figure 6: Power Profile on Q-core processor Device

3.2 Discussion

From the results presented, decreased power levels were observed near the foot of the tower, with higher levels towards the cell centre and lower levels towards the cell edge. For a base station whose cell radius spans 515m, Figure 1 shows better signal strength received at the cell centre (150m to 260m), but poor reception at the cell edge (350m to 515m) and towards the foot of the base station (<93m). It was observed that the presence of signal-scattering objects such as trees and high-rise buildings was a possible source of these anomalies at the cell centre. This trend can also be observed in Figure 3, as evaluated. At the cell edge, 515m from the primary base station, handover was implemented to an adjacent base station whose RSRP was about 3 dBm as against <-1 dBm from the primary base station. Degrading signal strength affected measured SINR quality, with the effect seen as we moved towards the cell edge for both networks. A channel with a better signal quality was sensed from an adjacent cell in the direction of motion (indicated in sky blue in Figures 1 and 2). Still, to our dismay, the handover sequence was only initiated in the test device once we were more than 515 m away from the primary eNB.

From Figure 3, at the cell edge, the latter half of the quad-core processors exhibited higher processor activities. However, their behaviour was similar at the cell centre, resulting in a less distinct response. During RT-voice applications (E and C voice calls), identical responses were observed and recorded for all the processor clocks, irrespective of location (cell edge or centre). Distinct processor clocking activities for nRT-video applications (E and C video streams) were also observed; however, there was no significant difference in these activities between the cell edge and the cell centre. Clocking speeds remained relatively consistent, even though the highly clocked sets of processors were alternated. In the cell centre, the initial sets of four processor sets operated at lower clock speeds compared to the second set of four, while at the cell edge, the first four sets had higher clock speeds. This observation did not support processors' additional power utilisation argument from the centre to the edge of the macrocell network. During video call applications from the cell centre to the cell edge (video call EC), the processor clocking was higher than in other applications.

The study also found that processors' activities did not significantly differ from cell centre to cell edge during power measurement and analysis of utilised energy. Power spikes occurred during RT-service deployment, and energy utilisation during UE idle mode was related to distance from the cell edge. RT-video call streaming consumed significantly more power than other deployed UE applications, classifying power levels as real-time (RT) and non-real-time (nRT). Video and voice calls showed significantly higher power utilisation than other services. In Figures 5 and 6, the impact of hardware systems along network variations was investigated, and it was demonstrated that real-time power consumption was marginally higher on Octa-core and Quad-core processors operating on 3G and 4G networks. The maximum power consumption observed in the active online mode of the 4G-enabled device exceeded that of its idle offline mode. Processor variations contributed significantly to power usage during idle offline mode, attributed to the device's hardware energy requirements. Octa-core processor-equipped devices exhibited distinctive energy consumption patterns across all deployed services, even offline.

4.0 CONCLUSION

This paper identifies energy requirements and application-specific energy consumption in mobile Internet of Things (IoT) applications. Real-time applications on mobile User Equipment (UEs) show higher energy consumption, particularly in the network's coverage area. The study suggests that processor activity remains consistent across observation points. Comparing different services deployed at a fixed location, the energy utilised has an apparent disparity one from another, i.e., RT services edged NRT services in terms of energy requirement across the network. However, hardware subsystems remain significant power consumers. The paper emphasizes the need for more energy-efficient systems in future IoT applications, emphasizing the importance of software and electronic engineers.

Future work will optimize energy utilisation and minimize consumption in IoT systems. This paper will assess application energy requirements and provide users with upfront information about anticipated energy consumption, addressing non-uniform energy usage in applications like video playback.

REFERENCES

[1] Dahunsi1, M., and Akinlabi, A. A. "Measuring Mobile Broadband Performance in Nigeria: 2G AND 3GF". Vol. 38, No. 2, 2019, pp.422–436 Copyright© Faculty of Engineering, University of Nigeria, Nsukka, Print ISSN: 0331-8443, Electronic ISSN: 2467-8821 http://dx.doi.org/10.4314/njt.v38i2.19

[2] Pilatso1, P., and Chukwuere, J. E. "Investigating the Impact of Fourth-Generation (4G) Mobile Technologies on Student Academic Performance", *Nigerian Journal of*

Technology, Vol. 41, No. 3, 2022, pp.547-559 Print ISSN: 0331-8443 Electronic ISSN: 2467-8821 http://dx.doi.org/10.4314/njt.v41i3.15

[3] Tawalbeh, M., Eardley, A., and Tawalbeh, L. "Studying the Energy Consumption in Mobile Devices," Procedia Computer Science, vol. 94, pp. 183-189, *The 13th International Conference on Mobile Systems and Pervasive Computing (MoniSPC 2016)*, 2016.

[4] Ladipo, O. I., and Gbenga-Ilori, A. O. "An Efficient Power Control Game Model for Wireless Sensor Networks", *Nigerian Journal of Technology*, vol. 38, no. 3, pp. 726–731, Jun. 2019, Accessed: Jun. 18, 2024. [Online]. Available: https://www.nijotech.com/index.php/nijotech/article/view/2065

[5] Ladipo, O. I and Gbenga-Ilori A. O. "A NonCooperative Power Control Game for Wireless Sensor Networks", *Nigerian Journal of Technology*, Vol. 38, No. 3, July 2019, pp. 726 – 731, Print ISSN: 0331-8443, Electronic ISSN: 2467-8821 http://dx.doi.org/10.4314/njt.v38i3.26

[6] El Outmani, A., Jaara, A., and Azizi, M. "Literature Review of Energy Consumption Modeling for Mobile Devices," in International Conference on Advanced Intelligent Systems for Sustainable Development (AI2SD 2022), Lecture notes in Networks and Systems, vol. 14, Springer, Cham, 2023, https://doi.org/10.1007/978-3-031-35245-4_9.

[7] Gokhale, A., Wang, W., and Dueskar, G. "Experimental Study of Power Consumption Characteristics for Wireless Multimedia Communication Apps in iOS Devices," in Proceedings of the 11th EAI International Conference on Mobile Multimedia Communications, EAI, Qingdao, 2018, https://doi.org/10.4108/eai.21-6-2018.2276546

[8] Cruz, L., and Abreu, R. "Catalog of Energy Patterns for Mobile Applications," Empir. Softw. Eng., vol. 24, no. 4, pp. 2209-2235, 2019, https://doi.org/10.1007/s10664-019-09682-0.

[9] Kazantsev, R., and Vatolin, D. "Power Consumption of Video Decoders on Various Android Devices," in 2021 Picture Coding Symposium (PCS), Bristol, United Kingdom, 2021, pp. 1-5, https://doi.org/10.1109/PCS50896.2021.9477481.

[10] Perrucci, G. P., Fitzek, F. H. P., and Widmer, J. "Survey on Energy Consumption Entities on the Smartphone Platform," 2011.

[11] Matyjaszek, H. "The Energy Impact of Mobile Phones," Energy Live News Ltd., 2021, https://www.energylivenews.com/2021/06/03/the-energy-impact-of-mobile-phones/.

[12] Dev, H. "Analysis of Power Consumption in a Smartphone," https://typexpersonality.medium.com/analysis-of-power-consumption-in-a-smartphone-ff327b8a5172, 2021.

[13] Tawalbeh, M., Eardley, A., and Tawalbeh, L. "Studying the Energy Consumption in Mobile Devices," 2016.

[14] Carroll, A., and Heiser, G. "Analysis of Power Consumption in a Smartphone," in USENIX Annual Technical Conference (USENIX ATC 10), 2010.

[15] Pramanik, P. K. D. et al., "Power Consumption Analysis, Measurement, Management, and Issues: A State-of-the-Art Review of Smartphone Batteries and Energy Usage," in IEEE Access, vol. 7, pp. 182113-182172, 2019, https://doi.org/10.1109/ACCESS.2019.2958684

[16] Elliot, J., Kor, A.-L., and Omotosho, O. A. "Energy Consumption in Smartphones: An Investigation of Battery and Energy Consumption of Media-Related Applications on Android Smartphones," Leeds Beckett Repository, www.eprints.leedsbeckett.ac.uk, 2017.

[17] Herglotz, C., Robitza, W., Kranzler, M., Kaup, A., and Raake, A. "Modeling of Energy Consumption and Streaming Video QoE Using a Crowdsourcing Dataset," in 14th International Conference on Quality of Multimedia Experience (QoMEX), Lippstadt, Germany, 2022, pp. 1-6, https://doi.org/10.1109/QoMEX55416.2022.9900886

[18] Bangash, A. A., Jamal, Q., Eng, K., Ali, K., and Hindle, A. "Energy Consumption Estimation of API Usage in Mobile Apps via Static Analysis," in 20th International Conference on Mining Software Repositories (MSR), pp. 5721-5730, 2023.

[19] Pandikumar, S., Sethupandian, S. B., Arovazhagan, B., and Rajeswari, P. "Towards Smartphone Energy Optimization Through Users' Operating Pattern Discovery," in Sentiment Analysis and Deep Learning: Proceedings of ICSADL 2022, pp. 615-627, 2023.

[20] Hamzaoui, K. I., Gabli, M., Mokhtari, A., and Dahmani, S. "Optimization of Energy Consumption of Mobile Devices," in 2021 International Conference on Electrical, Computer, Communications, and Mechatronics Engineering (ICECCME), Mauritius, 2021, pp.

01-06, https://doi.org/10.1109/ICECCME52200.2021.9590947
[21] Song, S., Wedyan, F., and Jararweh, Y. "Empirical Evaluation of Energy Consumption for Mobile Applications," in 2021 12th International Conference on Information and Communication Systems (ICICS), Valencia, Spain, 2021, pp. 352-357, https://doi.org/10.1109/ICICS52457.2021.9464579
[22] Andreucetti, R., Chen, S., Yuan, Z., and Muntean, G.-M. "Smartphone Energy Consumption of Multimedia Services in Heterogeneous Wireless Networks," in 2014 International Wireless Communications and Mobile Computing Conference (IWCMC), Nicosia, Cyprus, 2014, pp. 1147-1151, https://doi.org/10.1109/IWCMC.2014.6906516
[23] He, A., Srikanteswara, S., Bae, K. K., Reed, J. H., and Tranter, W. H. "Energy Consumption Minimization for Mobile and Wireless Devices - a Cognitive Approach," in IEEE Transactions on Consumer Electronics, vol. 56, no. 3, pp. 1814-1821, Aug. 2010, https://doi.org/10.1109/TCE.2010.5606331
[24] Hu, Z., and Ruutu, J. "Comparison of Energy Consumption Between a Mobile Device and a Collection of Dedicated Devices," in Proceedings of the 2011 IEEE International Symposium on Sustainable Systems and Technology, Chicago, IL, USA, 2011, pp. 1-6, https://doi.org/10.1109/ISSST.2011.5936873
[25] Kaup, F., and Hausheer, D. "Optimizing Energy Consumption and QoE on Mobile Devices," in 2013 21st IEEE International Conference on Network Protocols (ICNP), Goettingen, Germany, 2013, pp. 1-3, https://doi.org/10.1109/ICNP.2013.6733641
[26] Niemann, C., Ewert, C., Puttnies, H., Rethfeldt, M., Timmermann, D., and Danielis, P. "Modeling Energy Consumption for Task-Offloading Decisions on Mobile and Embedded Devices," in 2020 IEEE 2nd Global Conference on Life Sciences and Technologies (LifeTech), Kyoto, Japan, 2020, pp. 400-404, https://doi.org/10.1109/LifeTech48969.2020.1570618809
[27] Bernal, J. F. M., Ardito, L., Morisio, M., and Falcarin, P. "Towards an Efficient Context-Aware System: Problems and Suggestions to Reduce Energy Consumption in Mobile Devices," in 2010 Ninth International Conference on Mobile Business and 2010 Ninth Global Mobility Roundtable (ICMB-GMR), Athens, Greece, 2010, pp. 510-514, https://doi.org/10.1109/ICMB-GMR.2010.34
[28] Mohammed, A. F. E., Altayeb, M. H., and Osman, N. I. "Evaluating the Energy Efficiency of UE-to-Network Relay Assisted Device-to-Device Communication," in 2020 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), Khartoum, Sudan, 2021, pp. 1-5, https://doi.org/10.1109/ICCCEEE49695.2021.9429654
[29] Benson, M. E., Okafor, K. C., Ezema, L. S., Chuwkuchekwa, N., and Anthony, O. C. "Heterogeneous cyber-physical network coexistence through interference contribution rate and uplink power control algorithm (ICR-UPCA) in 6G edge cells" *Internet of Things*, Vol. 25, April 2024, 101031 https://doi.org/10.1016/j.iot.2023.101031
[30] Mubarakah, Naemah, and Suherman, "Reducing Mobile Device Energy Consumption in Transmitting Multimedia Content by Arranging Transport Protocol Load," in 2016 International Seminar on Application for Technology of Information and Communication (ISemantic), Semarang, Indonesia, 2016, pp. 111-113, https://doi.org/10.1109/ISEMANTIC.2016.7873819.
[31] Oliveira, T. R. B., Ursini, E. L., and Timoteo, V. S. "Simulation-Based Assessment of Energy Consumption Optimization in 3G Mobiles," in 2011 International Conference on Computer and Management (CAMAN), Wuhan, China, 2011, pp. 1-5, https://doi.org/10.1109/CAMAN.2011.5778753.
[32] Riaz, M. N. "Energy Consumption in Hand-Held Mobile Communication Devices: A Comparative Study," in 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), Sukkur, Pakistan, 2018, pp. 1-5, https://doi.org/10.1109/ICOMET.2018.8346333.
[33] Hamzaoui, K. I., Gabli, M., Mokhtari, A., and Dahmani, S. "Optimization of Energy Consumption of Mobile Devices," in 2021 International Conference on Electrical, *Computer, Communications, and Mechatronics Engineering (ICECCME)*, Mauritius, 2021, pp. 01-06, https://doi.org/10.1109/ICECCME52200.2021.9590947
[34] Song, S., Wedyan, F., and Jararweh, Y. "Empirical Evaluation of Energy Consumption for Mobile Applications," in 2021 12th *International Conference on Information and Communication Systems (ICICS)*, Valencia, Spain, 2021, pp. 352-357, https://doi.org/10.1109/ICICS52457.2021.9464579.