IMPACT OF USER CONTEXT ACTIVITIES ON POWER CONSUMPTION DURING HANDOVER IN NEW GENERATION WIRELESS NETWORKS

Vinodini Guptan and Padma Bonde
Shri Shankaracharya Technical Campus, Bhilai, Chhattisgarh, India
gupta.vinu9@gmail.com and bondepadma@gmail.com

ABSTRACT

With rapid growth of digital dependency and networking technologies, and Human-Computer Interaction (HCI) has become a key component of new generation ubiquitous networking. Achieving a high Quality of Experience (QoE) for users has become crucial and challenging Context Aware Computing (CAC), which uses contextual data to improve network adaptability and user satisfaction, must be considered an important factor in wireless networking especially during handover. This paper presented impact of different user context activities on wireless node power consumption, during the handoff in next-generation wireless networks to improve Quality of Content (QoC) and realize energy efficient networking protocols. It presented a methodology to evaluate the effect of scalability on power consumption of wireless nodes and network performance. Scenario of Vertical handover scenario between WiFI and WiMAX network was simulated over NS2 for two sets of wireless nodes namely Type-I and Type-II nodes. Various user activities like browsing, web streaming, E-Commerce etc. were considered in the study. The energy usage of wireless nodes power was analyzed at three different voltage levels i.e. charge voltage, nominal voltage and cutoff voltage. Network performance under given networking conditions for power constrained context computing is analyzed in terms of Residual energy, Throughput and Packet Delivery Ratio (PDR). The results showed the pattern of battery drainage in wireless nodes due to various simultaneously ongoing user context activities during handover. This study will provide basic framework to improvise networking technologies for achieving sustainable Green Networking.

Keywords: *User Context, Green Networking, Context Aware Computing, Power Consumption, Throughput and Packet Delivery Ratio.*

1. INTRODUCTION

With the outbreak of technological revolution, dependency on digital data is increasing day by day. With this there is constant demand of seamless communication in addition to enhanced user experience. Wireless networking therefore plays crucial role in almost every sphere of human life. Since wireless devices are power constrained, maintaining Quality of Service (QoS), Quality of Experience(QoE) and network performance simultaneously especially during handover[1] is crucial. Considering user experience, Context Aware Computing (CAC) plays important role in determining the overall performance of wireless networks.

Quality of Experience (QoE) basically deals with over all user satisfaction during wireless communication to meet their expectation within their perception. Quality of Content (QoC) is a decisive factor in determining the levels of user satisfaction. To enhance the user context quality Context Aware Computing (CAC) should be well incorporated in the networking protocols leading to improved user experience during ubiquitous communication.

Power consumption is an important factor in deciding the network performance. Wireless nodes operates on battery and therefore are highly energy constrained. So achieving desirable network performance along with enhanced user experience in an energy constrained networking scenario demands energy conservation especially during handover. This research therefore aims at devising context-aware energy efficient algorithms for sustainable Green Networking.(GN). The further organization of paper comprises discussions on importance of Context Aware Computing during wireless communications in Section 2. Power consumption estimation in a context aware handover scenario is discussed in Section 3. Section 4 focused on simulation details and experimental setup. Section 5 discussed the pattern of power consumption and network performance metrics obtained during the simulation. Finally, conclusions were drawn in Section 6.

2. IMPORTANCE OF CONTEXT COMPUTING IN NEW GENERATION UBIQUITOUS NETWORKS

User Experience is one of the crucial factor in deciding the network performance and efficiency of network during handover. Quality of Experience is highly affected by the context aware computing (CAC). Also. Wireless nodes are battery constrained and so context aware energy efficient mechanisms [2] are need of hour to achieve higher standards of user satisfaction. In present era, it is therefore necessary to integrate context computing in ubiquitous networking scenario. In this context[3] presented a survey on integrating context aware computing in wireless networking to enhance multimedia service delivery. It discussed methodology, challenges and mechanism s of context aware networking.[4] also discussed the challenges in context aware computing and their potential solutions for realizing efficient computing environment in future. CAC yet important in efficiency and smooth functioning of IoTSystems.[5] discussed overview of context life cycle in IoT systems to lay down efficient context aware framework for future IoT ecosystems. Similarly [6] presented a survey over context aware computing highlighting classification framework based on Context Acquisition, Context Modeling, Context Reasoning and Context Distribution.[7] reviewed various distribution models and provided review of context data distribution mechanisms in mobile and ubiquitous computing environments.[8] discussed various real-world applications enabled by activity recognition on mobile devices, such as Healthcare monitoring , Elder care and assisted living, Context-aware services, Smart environments, Personal behavior analysis and lifestyle feedback etc. A comprehensive review of affective sensing technologies that detect human emotions is presented in [9] which discussed key challenges such as sensor accuracy, data fusion, privacy and ethics, related to emotional interpretation.

Managing the resources and dynamic data in wireless networking is extremely essential and CAC plays crucial role in managing such data. A policy based management strategy is proposed in [10] to cope up with the infrastructure and service management challenges occurring in context aware distributed systems. Similarly, a context management architecture is proposed in [11] to manage dynamic context data in adaptive applications to deliver relevant context with minimal overhead.[12] proposed context aware framework for efficient resource management in ubiquitous LTE Networks.[13] proposed a context-aware user association model, where context data leads to more efficient and stable network performance, especially in dense and dynamic heterogeneous network environments.

User satisfaction is one of the important factor for determining the performance of ubiquitous networks. In this context,[14] discussed various strategies such as cross-layer coordination, context-awareness, and QoE-based management. to enhance Quality of Experience(QoE)in heterogeneous wireless networks. Similarly,[15] proposed machine learning-driven handover management technique that uses ML algorithms that optimizes handover performance based on certain metrics such as mobility, context data, QoE standards and other network performance metrics.

Quality of Service (QoS) is equally important metrics in determining the performance of network especially during handover. For this[16] proposed a context aware decision algorithm that uses load aware strategy in controlling traffic during vertical handover to prevent congestion thereby improving the QoS.[17] proposed context-aware mobility management framework for intelligent handover decision making to achieve better QoS and QoE and energy efficient offloading in eHealth WBANs by taking into account various context information related to underlying network and patients. For better network selection,[18] proposed context-aware network selection framework for selecting most appropriate access point during handoff by considering real time contextual information related to user, network and application. Yet another context aware decision framework is proposed in [19] that uses cross-layer monitoring and a utility-based decision model to ensure better QoS and QoE by reducing the occurrences of unnecessary handovers.[20] proposed a context-aware framework to optimize energy consumption and enhance QoS by implementing adaptive resource allocation strategy based on context information such as user context, network conditions and service requirements. To improve the efficiency and reliability of vertical handoffs [21] implemented location awareness strategy for location based handoff decision model that uses context information like Geographic location and movement trajectory, cell overlapping, network conditions and QoS and QoE requirements. [22] proposed yet another context aware handover decision framework to provide reliable and seamless healthcare services by considering context information like patient context, network context and device and application context.

Furthermore [23] proposed a utility-based decision-making model for dynamic network selection algorithm by using real time context information such as user context, network context, application requirements and environmental context that significantly improves handover efficiency, QoS, and user satisfaction, while minimizing service disruption and unnecessary handovers. To enhance system performance and context reasoning accuracy a context-aware aggregate strategy is proposed in [24] to cope up with the challenges of dynamic and heterogeneous contextual data. Similarly, [25] proposed a ML based system for context classification to improve contextual data security and usability. Moreover, a mobility prediction model was proposed in[26] to predict future locations and movements of user to provide better QoS and QoE standards.[27] discussed the utility of 5G capabilities to dynamically adapting user needs and environment through context aware computing.[28] introduced a novel model for handling dynamic context updates through efficient memory management by optimizing the working memory component of context-aware systems for enhancing network performance in scalable ubiquitous environment.

3. POWER CONSUMPTION DUE TO VARIATIONS IN USER CONTEXT ACTIVITIES:-

User experience in wireless networking can be increased by incorporating Context Aware Computing CAC) with energy efficient networking techniques. Power consumption in context aware networking scenario can be highly variable due to multiple user context activities ongoing at user site simultaneously especially during handover. The steps for analyzing cumulative power consumption of wireless nodes due to multiple user context activities during handover in context aware networking environment is depicted in Figure 3.1

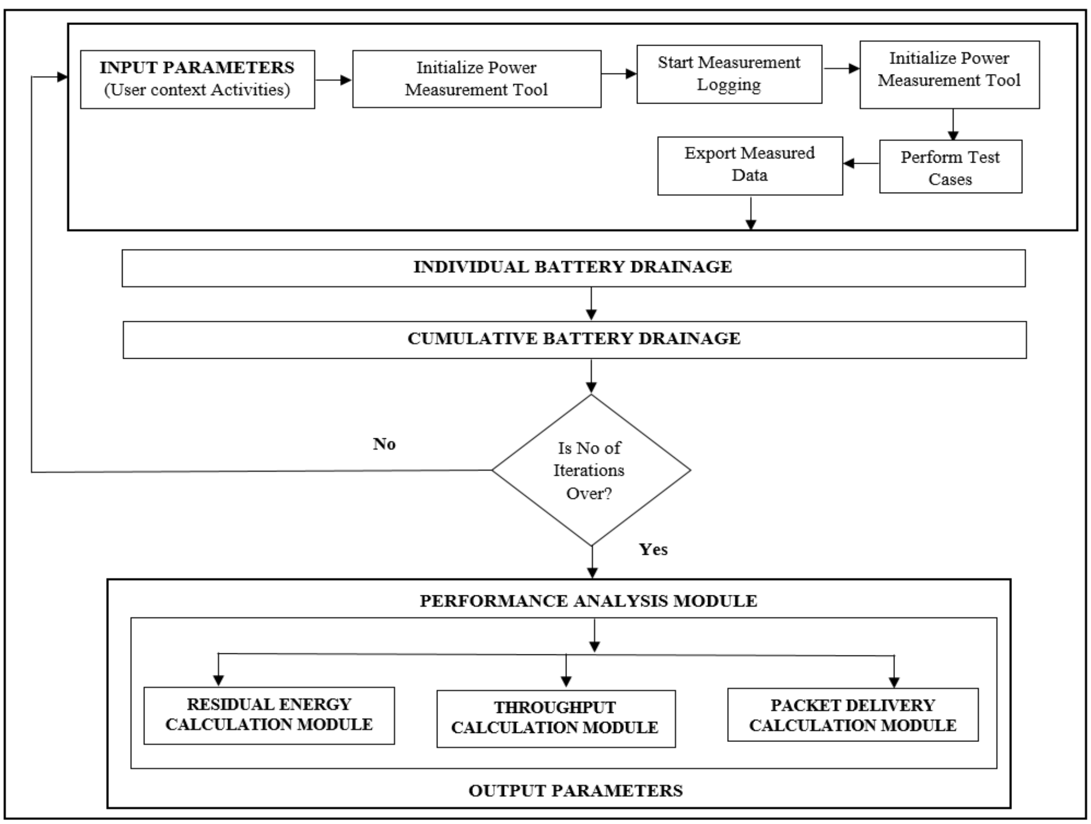


Figure.3.1: Essential steps for analyzing cumulative power consumption due to user context activities in wireless networking

It begins with input parameters involving various user-related activities and behaviours, such as app usage patterns, location tracking, browsing, E-commerce and other contextual interactions. These activities are measured by initializing a power measurement tool and measuring the activity log data followed by test cases performance. The measured data is then exported for analysis. Each stage may contribute to battery usage differently and power consumption due to these activities is first evaluated in the Individual Battery Drainage Module, and then combined in the Cumulative Battery Drainage Module to assess the total power consumption caused by continuous context monitoring. This analysis is continuously recorded over certain number of iterations. Upon completion, performance analysis is done using Performance Analysis Module, which calculates Residual Energy, Throughput and Packet Delivery Ratio. This framework supports the development of energy-efficient, context-aware networking techniques.

Power consumption due to various user context activities is calculated using "Battery Guru" App to analyse the effect of user context on overall power consumption during handoff. Various user activities considered for power calculation are calling, browsing, file transfer, gaming, live streaming, video streaming, video conferencing, chatting applications, e-commerce applications, editing applications and banking applications. The average power ($P_{(UserAh(avg))}$) and the standard power ($P_{(UserAh(std))}$) in Ampere-hour at a given voltage V (in volts) consumed during handoff for n number of context activities can be calculated from equation 1 and equation 2 respectively.

$$P_{UserAh(avg)} = \frac{1}{n} \times \sum_{i=1}^{n}(P_i) \quad (1)$$

$$P_{UserAh(std)} = \sqrt{\frac{1}{n} \times \sum_{i=1}^{n}(P_i - P_{User(avg)})^2} \quad (2)$$

3.1.1. Cumulative Power Consumption

Average power consumption $P_{TotalAh(avg)}$ (in Ampere-hour) and standard power consumption $P_{TotalAh(std)}$ (in Ampere-hour) at a specified voltage (V) are calculated for m iterations to analyze the cumulative effect of n parameters variations over the power consumption pattern of wireless nodes under different scenarios during handover to estimate corresponding battery drainage as given in equation 3 and equation 4.

$$P_{CummAh(avg)} = \sum_{i=1}^{m} \frac{1}{m} \times \sum_{j=1}^{n}\left(P_{Ah(avg)_j}\right) \quad (3)$$

$$P_{CummAh(std)} = \sum_{i=1}^{m} \frac{1}{m} \times \sqrt{\frac{1}{n} \times \sum_{j=1}^{n}(P_{Ah(avg)_j} - P_{CummAh(avg)})^2} \quad (4)$$

4. EXPERIMENTAL SETUP

In the proposed methodology, handoff scenario between wi-fi technology (ieee 802.11n standards) and wimax (ieee 802.16 standards) technology was implemented using network simulator software (ns-2) for analyzing the impact of user context activities over power consumption in wireless networks. The simulation scenario is shown in figure 4.1 and other simulation specifications are mentioned in table 4.1 below.

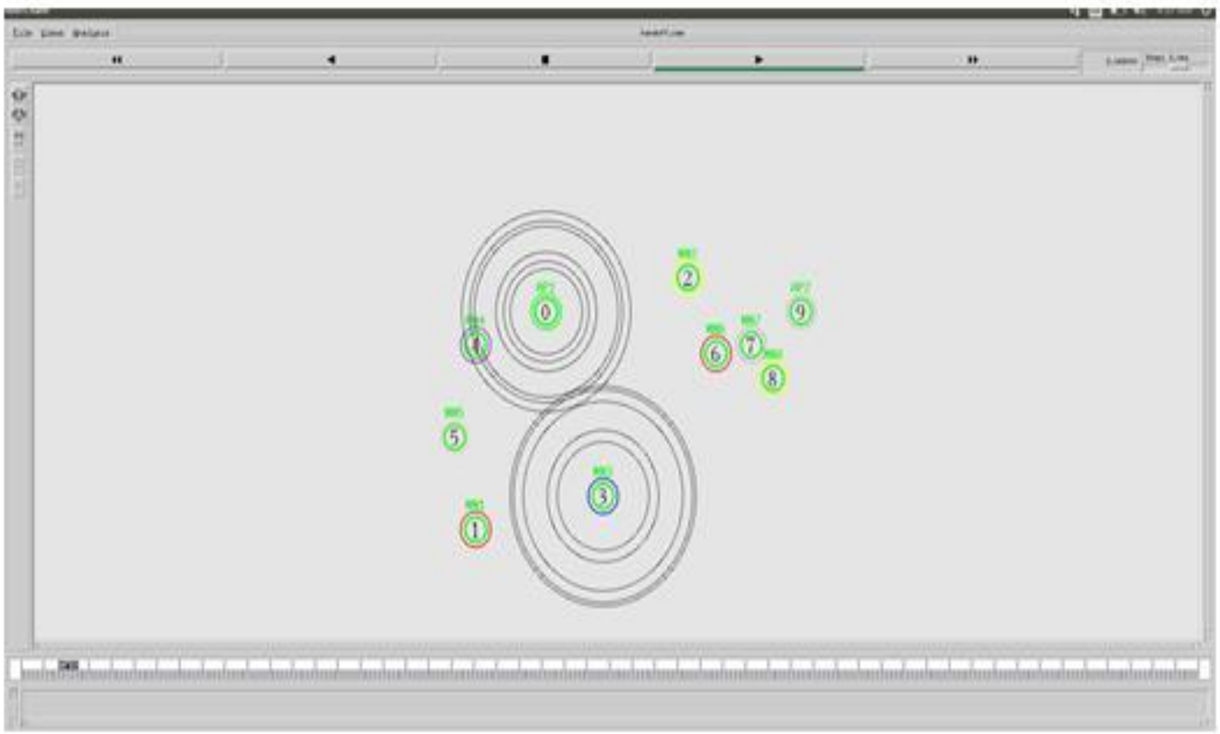


Figure.4.1. Simulation Scenario

Table 3.1. Simulation Parameters

Configuration	Parametric Values
Simulation Area	600 * 600
Access Points	2
Number of Nodes	10
Propagation Model	Two Ray Ground
Traffic Type	CBR
Packet Size	1023 bytes
Bandwidth	1 Mbps
Voltage Levels	4.2V, 3.7V and 3.2V

A 3500 mAh Li-ion battery of 3.7 volts is considered as Type-I nodes and a 4 cell Li-ion battery of 3500 mAh capacity and 14.8 volts is considered as Type-II nodes. During the simulation, various context activities like E-Commerce applications, banking applications, OTT applications, messaging applications, conferencing applications, browsing, calling, Bluetooth transfer, file transfer and editing applications. Three different voltage levels namely charge voltage (4.2V), nominal voltage (3.7V), and a cut-off voltage (3.2V). Under experimental conditions, other factors affecting the power consumption of nodes are considered to be negligible.

5. RESULT ANALYSIS AND DISCUSSION

5.1 Result Analysis

Figure 5.1 illustrates the variation in power consumption for user context activity during Bluetooth and file transfers. For Bluetooth transfers, the average power consumption for Type-I and Type-II nodes was 0.517 Ah and 2.070 Ah at charge voltage, 0.587 Ah and 2.350 Ah at nominal voltage, and 0.598 Ah and 2.393 Ah at cut-off voltage. Similarly, for file transfers, the average power consumption for Type-I and Type-II nodes was 0.476 Ah and 1.905 Ah at charge voltage, 0.540 Ah and 2.163 Ah at nominal voltage, and 0.625 Ah and 2.501 Ah at cut-off voltage.

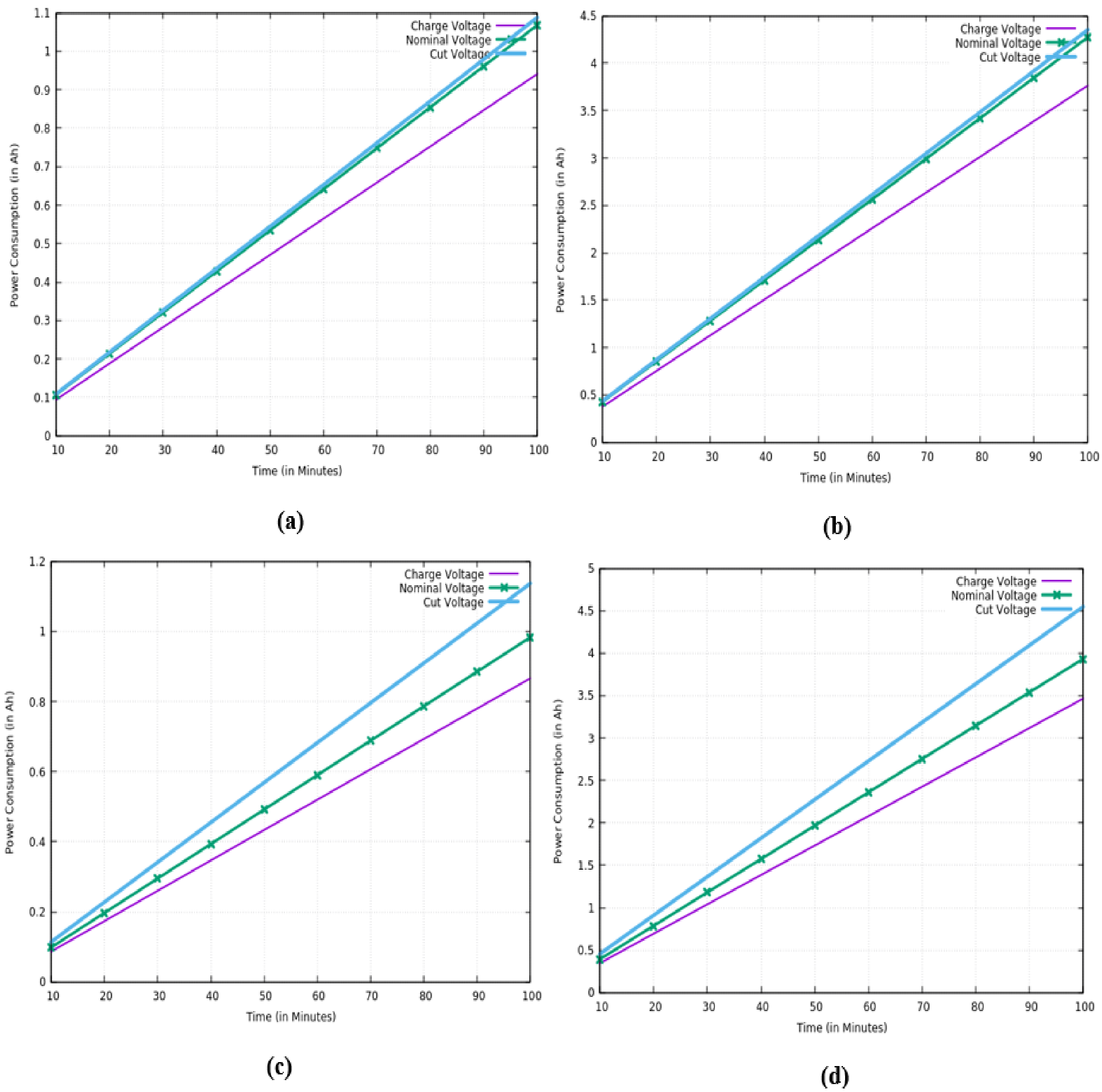


Figure 5.1. Variation of power consumption due to user context activity (a) For Bluetooth transfer for Type-I nodes. (b) For Bluetooth transfer for Type-II nodes. (c) For File transfer for Type-I nodes. (d) For File transfer for Type-II nodes.

Figure 5.2 illustrates the variation in power consumption for user context activity during Banking App and Shopping App. For Banking App, the power consumption for Type-I and Type-II nodes was 0.504Ah and 2.016 Ah at charge voltage, 0.572 Ah and 2.288 Ah at nominal voltage, and 0.661 Ah and 2.64 Ah at cut-off voltage. Similarly, for Shopping App, the power consumption for Type-I and Type-II nodes was 0.506 Ah and 2.026 Ah at charge voltage, 0.575 Ah and 2.300 Ah at nominal voltage, and 0.664 Ah and 2.659 Ah at cut-off voltage.

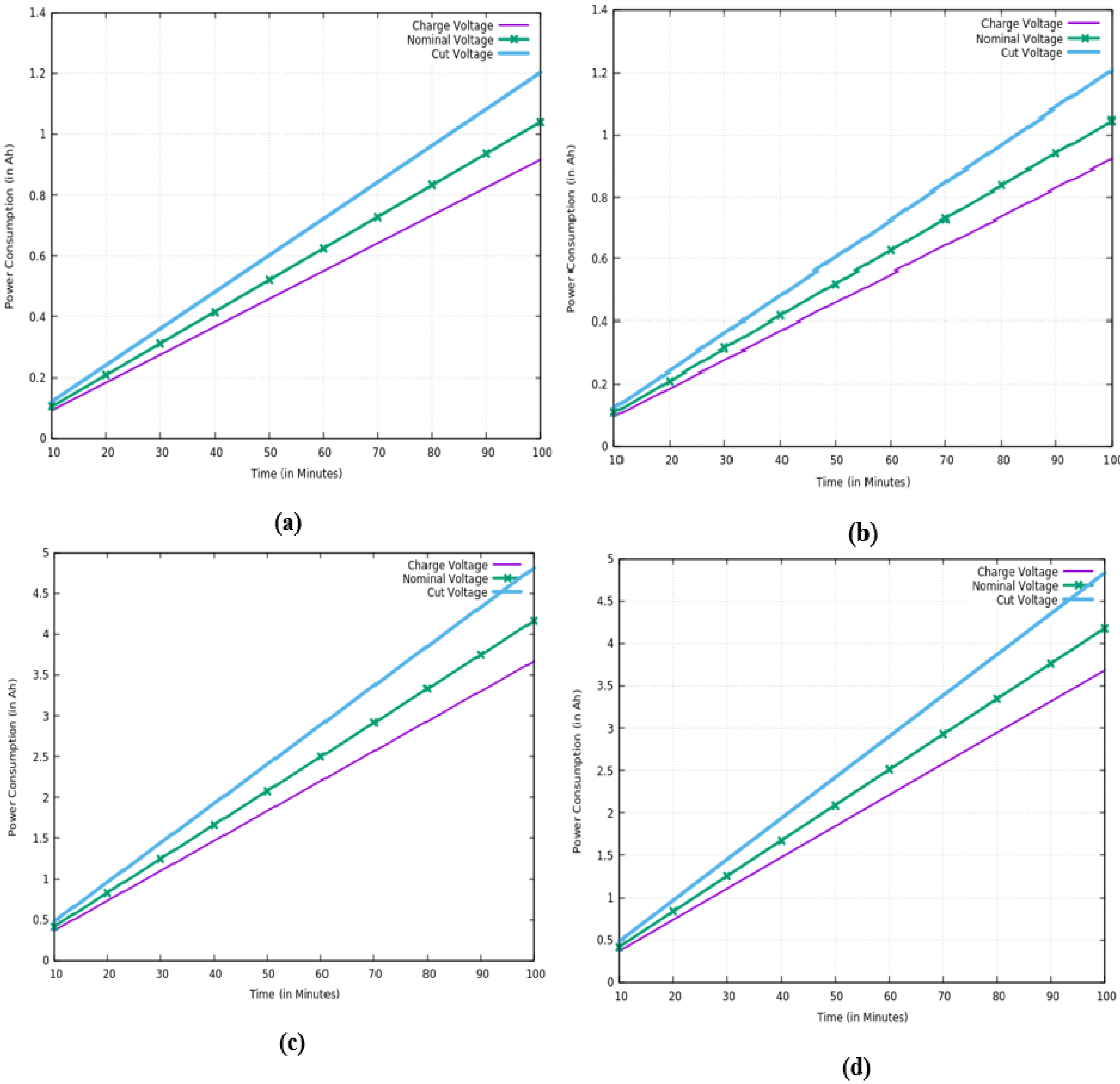


Figure 5.2. Variation of power consumption due to user context activity (a) For Banking App for Type-I nodes. (b) For Banking App for Type-II nodes. (c) For Shopping App for Type-I nodes. (d) For Shopping App for Type-II nodes.

Figure 5.3 illustrates the variation in power consumption for user context activity during Calling and Messaging. For Calling, the power consumption for Type-I and Type-II nodes was 0.333 Ah and 1.333 Ah at charge voltage, 0.378 Ah and 1.513 Ah at nominal voltage, and 0.437 Ah and 1.749 Ah at cut-off voltage. Similarly, for Messaging, the power consumption for Type-I and Type-II nodes was 0.588 Ah and 2.237 Ah at charge voltage, 0.635 Ah and 2.540 Ah at nominal voltage, and 0.734 Ah and 2.937 Ah at cut-off voltage.

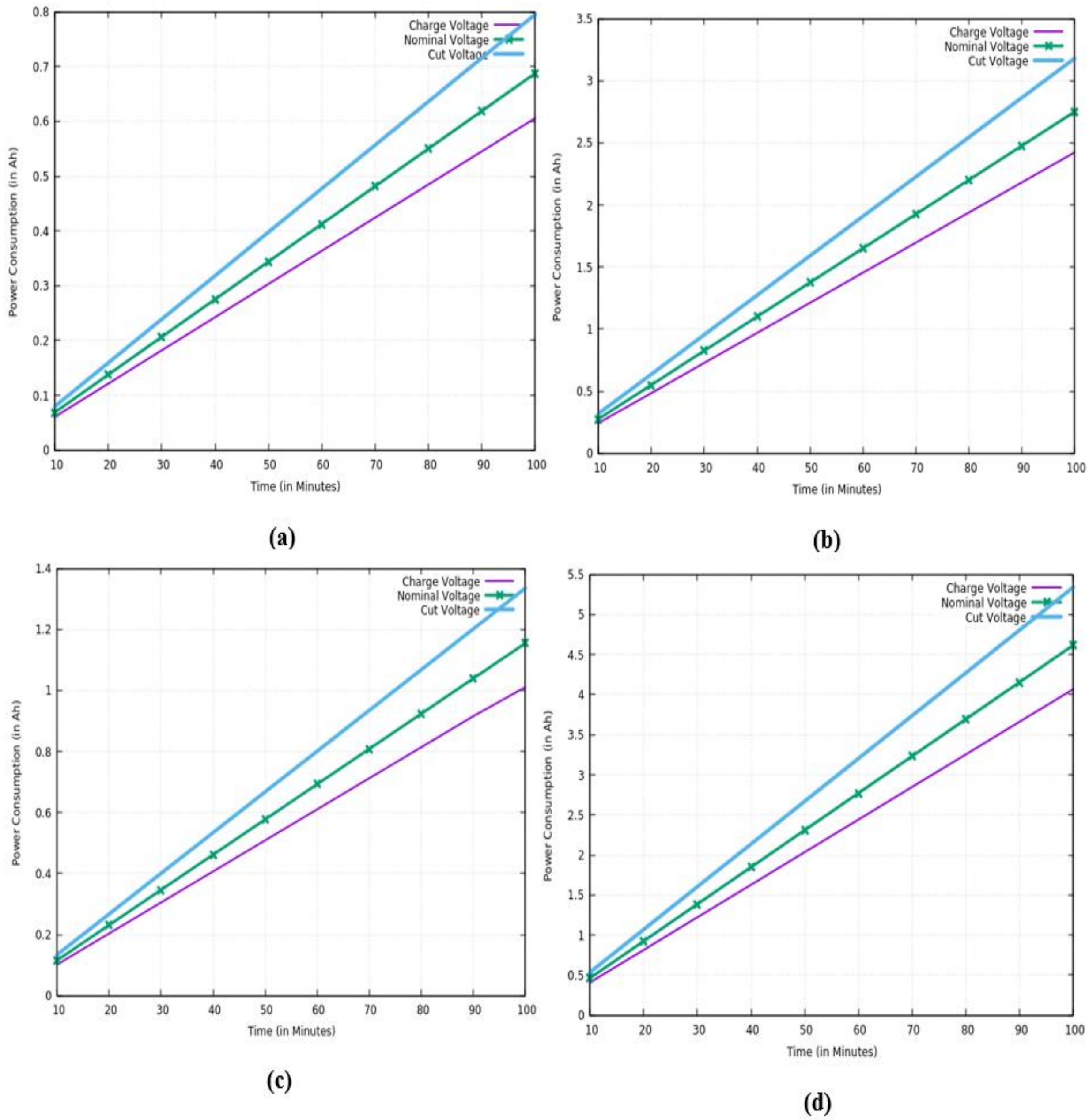


Figure 5.3. Variation of power consumption due to user context activity (a) For Calling for Type-I nodes. (b) For Calling for Type-II nodes. (c) For Messaging for Type-I nodes. (d) For Messaging for Type-II nodes.

Figure 5.4 illustrates the variation in power consumption for user context activity during Gaming App and OTT App. For Gaming App, the power consumption for Type-I and Type-II nodes was 0.543 Ah and 2.172 Ah at charge voltage, 0.616 Ah and 2.465 Ah at nominal voltage, and 0.712 Ah and 2.850 Ah at cut-off voltage. Similarly, for OTT App, the power consumption for Type-I and Type-II nodes was 0.459 Ah and 1.836 Ah at charge voltage, 0.521 Ah and 2.084 Ah at nominal voltage, and 0.602 Ah and 2.410 Ah at cut-off voltage.

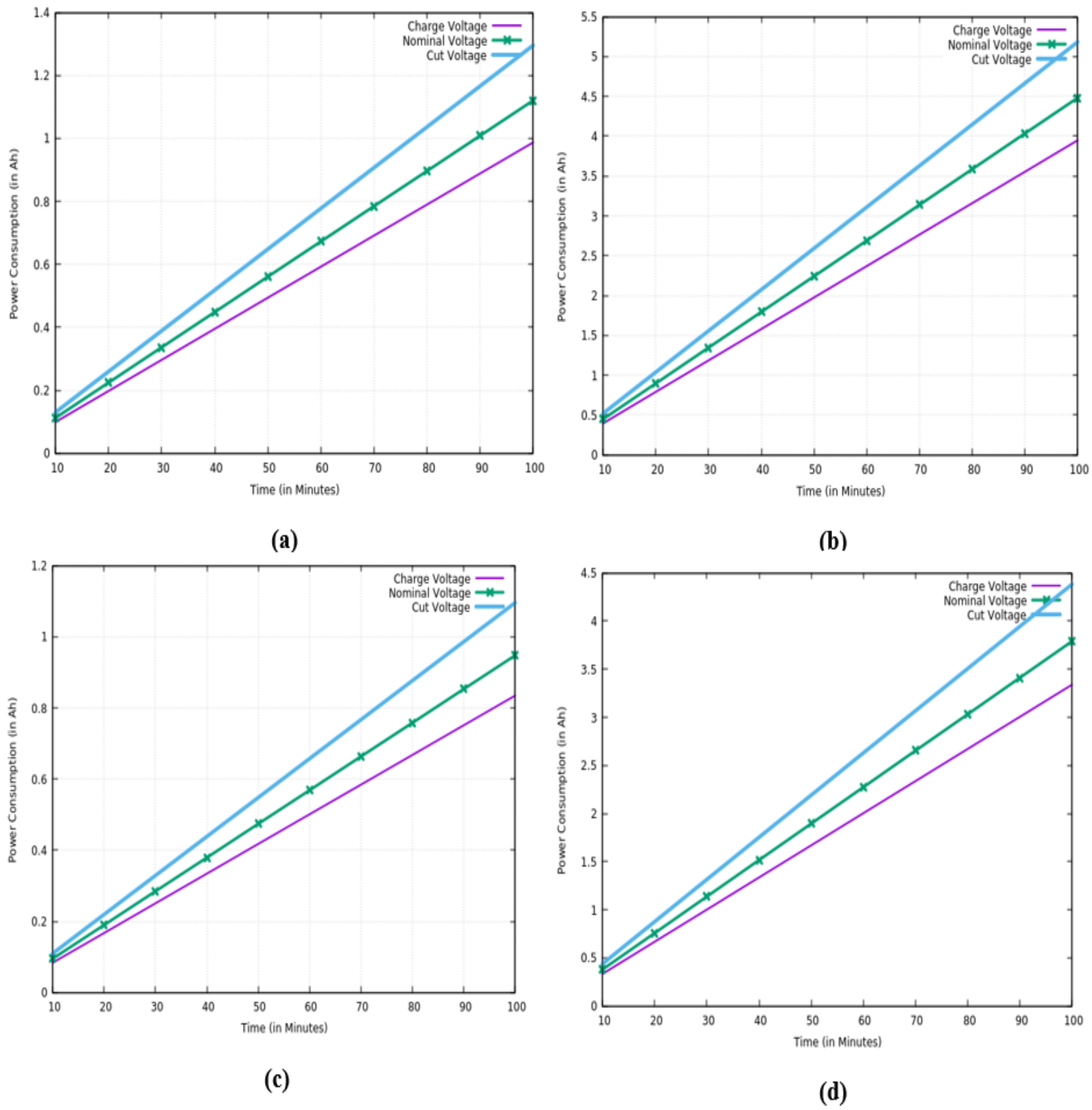
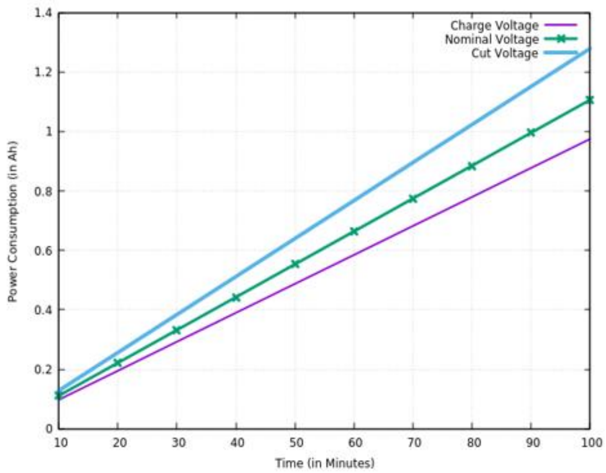
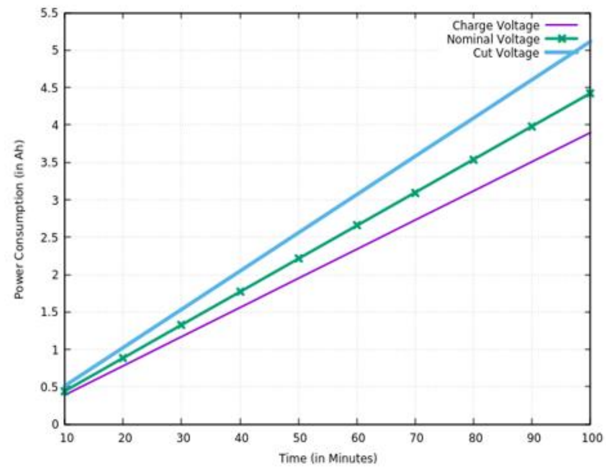


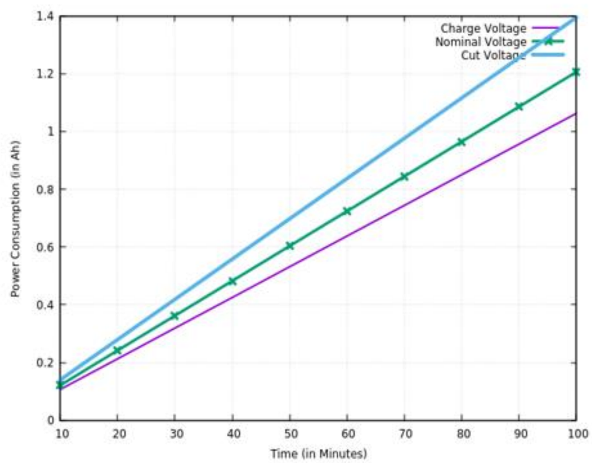
Figure 5.4. Variation of power consumption due to user context activity (a) For Gaming App for Type-I nodes. (b) For Gaming App for Type-II nodes. (c) For OTT App for Type-I nodes. (d) For OTT App for Type-II nodes.



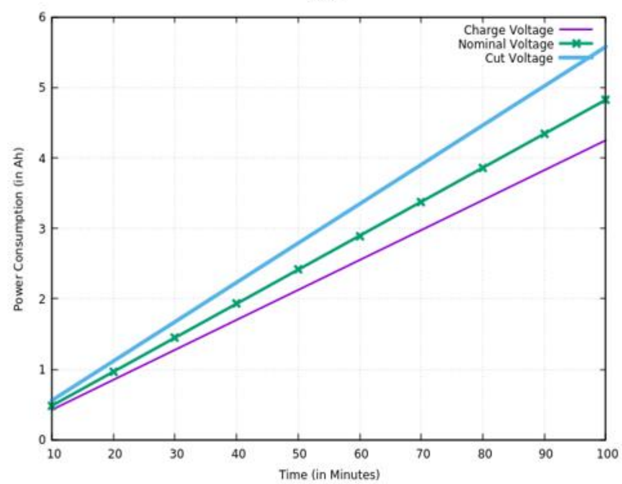
(a)



(b)



(c)



(d)

Figure 5.5. Variation of power consumption due to user context activity (a) For Conferencing App for Type-I nodes. (b) For Conferencing App for Type-II nodes. (c) For Editing App for Type-I nodes. (d) For Editing App for Type-II nodes.

Figure 5.5 illustrates the variation in power consumption for user context activity during Conferencing App and Editing App. For Conferencing App, the power consumption for Type-I and Type-II nodes was 0.536 Ah and 2.144 Ah at charge voltage, 0.608 Ah and 2.434 Ah at nominal voltage, and 0.703 Ah and 2.814 Ah at cut-off voltage. Similarly, for Editing App, the power consumption for Type-I and Type-II nodes was 0.584 Ah and 2.337 Ah at charge voltage, 0.663 Ah and 2.653 Ah at nominal voltage, and 0.766 Ah and 3.067 Ah at cut-off voltage.

Figure 5.6(a) and Figure 5.6(b) illustrates the variation in power consumption for user context activity during Browsing. The average power consumption was 0.713 Ah and 2.855 Ah at charge voltage, 0.810 Ah and 3.241 Ah at nominal voltage, and 0.937 Ah and 3.748 Ah at cut-off voltage. Similarly, Figure 5.6(c) and Figure 5.6(d) illustrates the cumulative power consumption for user context activity for Type-I and Type-II nodes. The cumulative power consumption for Type-I and Type-II nodes was 6.99 Ah and 27.861 Ah at charge voltage, 7.906 Ah and 31.626 Ah at nominal voltage, and 9.061 Ah and 36.244 Ah at cut-off voltage.

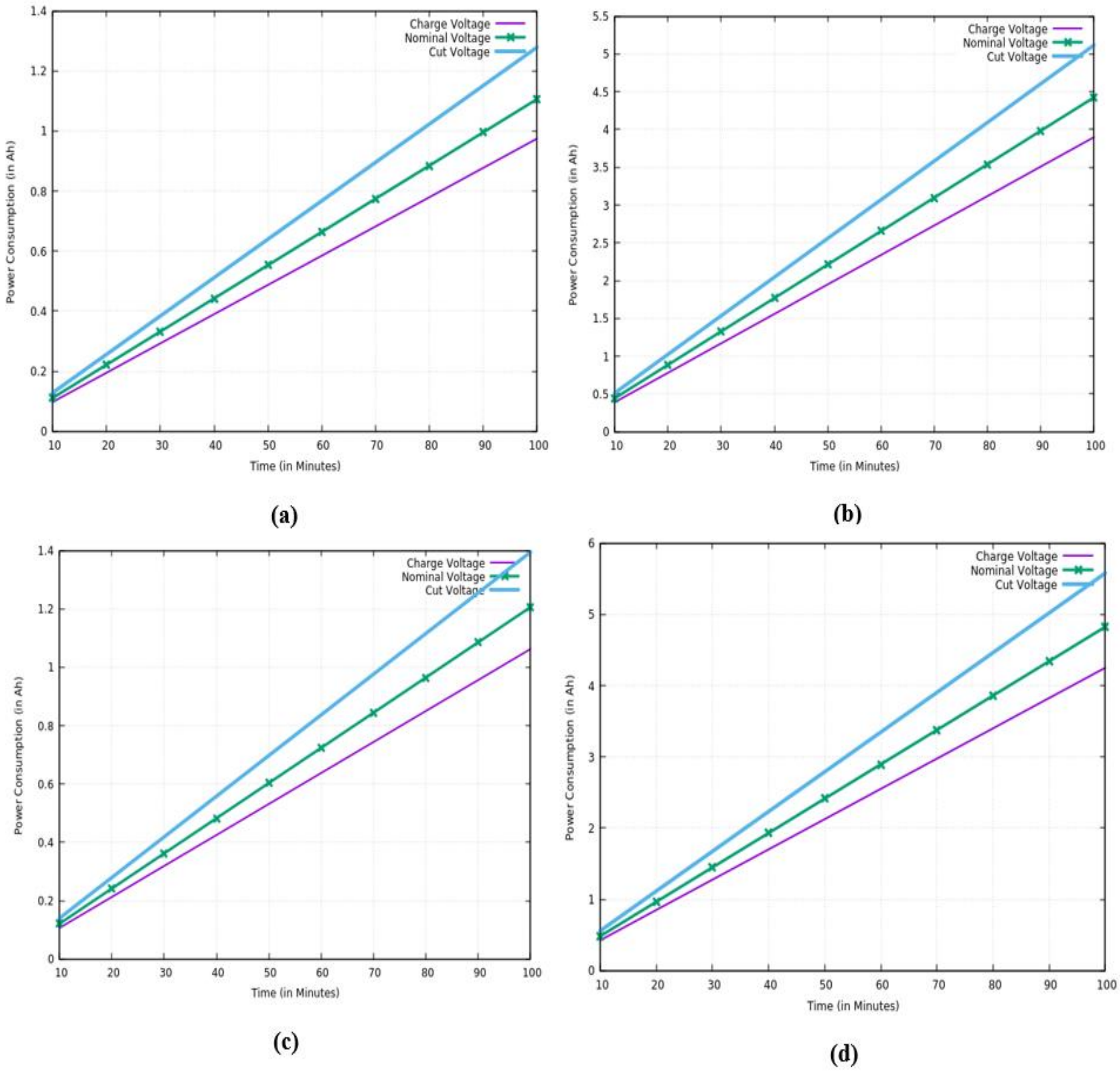


Figure 5.6. Variation of power consumption due to user context activity (a) For Browsing for Type-I nodes. (b) For Browsing for Type-II nodes. (c) Cumulative power consumption for Type-I nodes. (d) Cumulative power consumption for Type-II nodes

Figure 5.7 illustrates the variation in residual energy for user context activity during Bluetooth and file transfers. For Bluetooth transfers, the average residual energy for Type-I and Type-II nodes was 2.98 Ah and 11.92 Ah at charge voltage, 2.91 Ah and 11.64 Ah at nominal voltage, and 2.90 Ah and 11.60 Ah at cut-off voltage. Similarly, for file transfers, the average residual energy for Type-I and Type-II nodes was 3.02 Ah and 12.09 Ah at charge voltage, 2.95 Ah and 11.83 Ah at nominal voltage, and 2.87 Ah and 11.49 Ah at cut-off voltage.

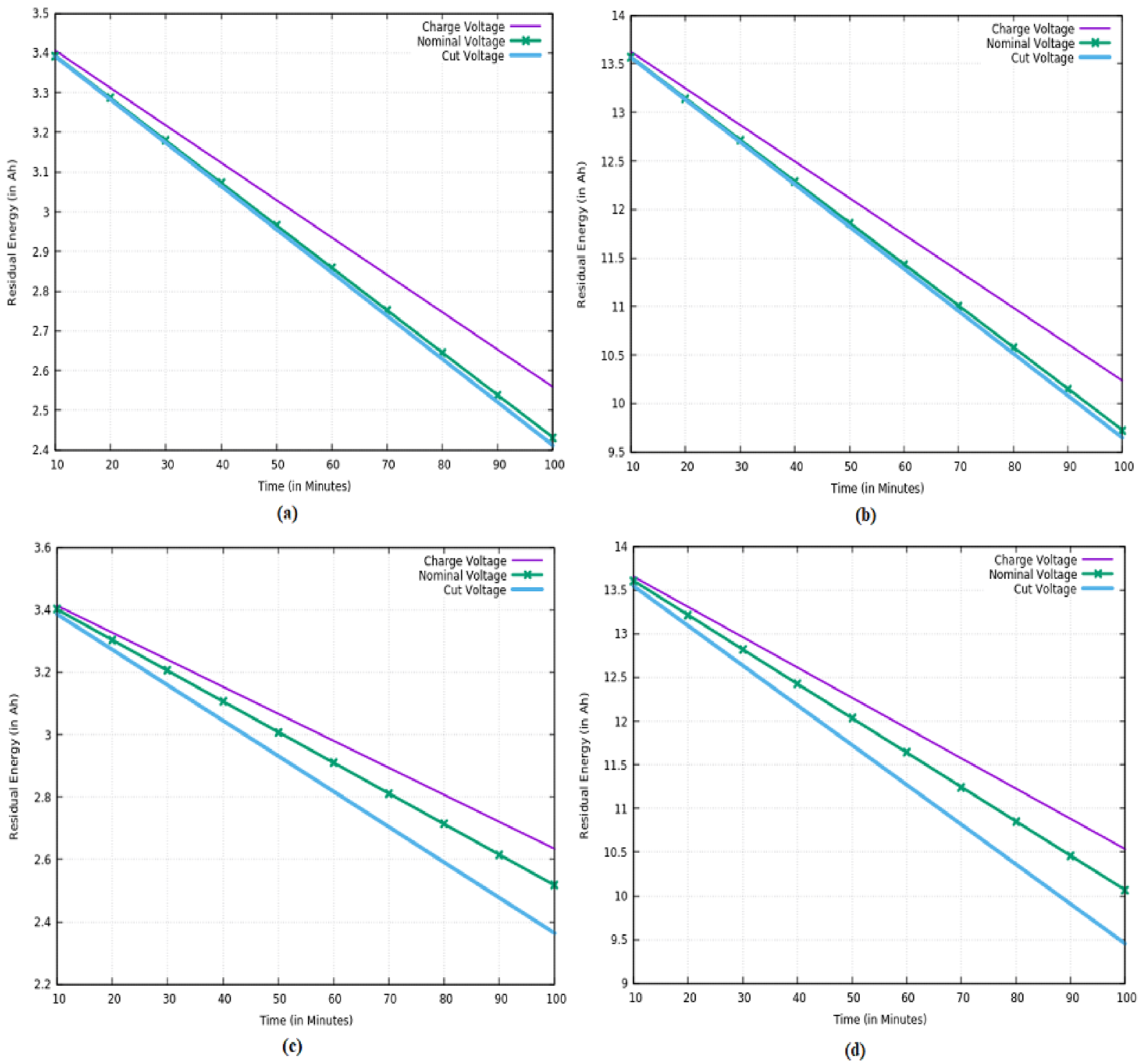


Figure 5.7. Variation of residual energy due to user context activity (a) For Bluetooth transfer for Type-I nodes. (b) For Bluetooth transfer for Type-II nodes. (c) For File transfer for Type-I nodes. (d) For File transfer for Type-II nodes.

Figure 5.8 illustrates the variation in residual energy for user context activity during Banking App and Shopping App. For Banking App, the residual energy for Type-I and Type-II nodes was 2.99 Ah and 11.98 Ah at charge voltage, 2.92 Ah and 11.71 Ah at nominal voltage, and 2.83 Ah and 11.35 Ah at cut-off voltage. Similarly, for Shopping App, the residual energy for Type-I and Type-II nodes was 2.99 Ah and 11.97 Ah at charge voltage, 2.92 Ah and 11.69 Ah at nominal voltage, and 2.83 Ah and 11.34 Ah at cut-off voltage.

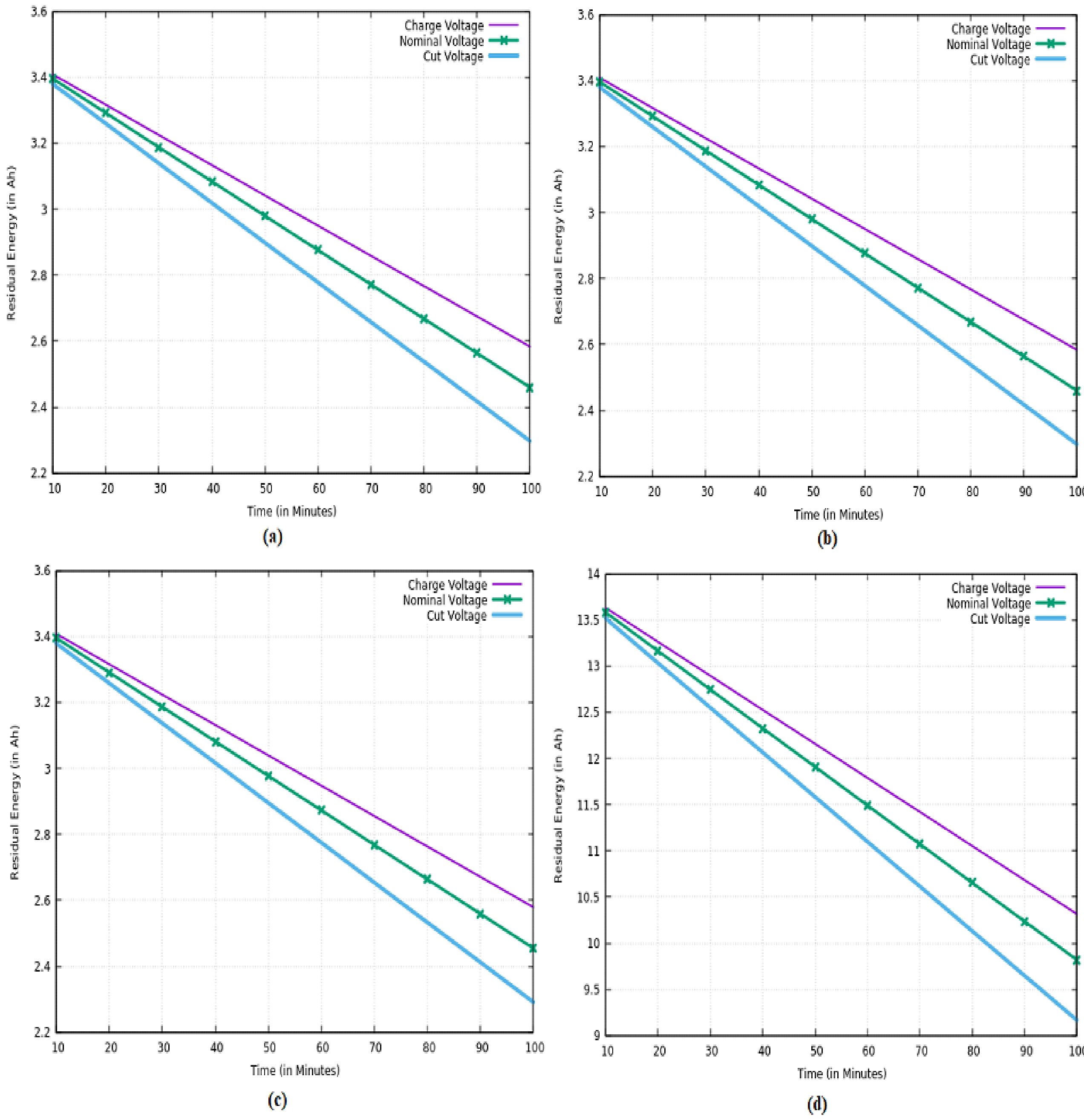


Figure 5.8. Variation of residual energy due to user context activity (a) For Banking App for Type-I nodes. (b) For Banking App for Type-II nodes. (c) For Shopping App for Type-I nodes. (d) For Shopping App for Type-II nodes.

Figure 5.9 illustrates the variation in residual energy for user context activity during Calling and Messaging. For Calling, the residual energy for Type-I and Type-II nodes was 3.166 Ah and 12.66 Ah at charge voltage, 3.12 Ah and 12.48 Ah at nominal voltage, and 3.06 Ah and 12.25 Ah at cut-off voltage. Similarly, for Messaging, the residual energy for Type-I and Type-II nodes was 2.91 Ah and 11.76 Ah at charge voltage, 2.86 Ah and 11.45 Ah at nominal voltage, and 2.76 Ah and 11.06 Ah at cut-off voltage.

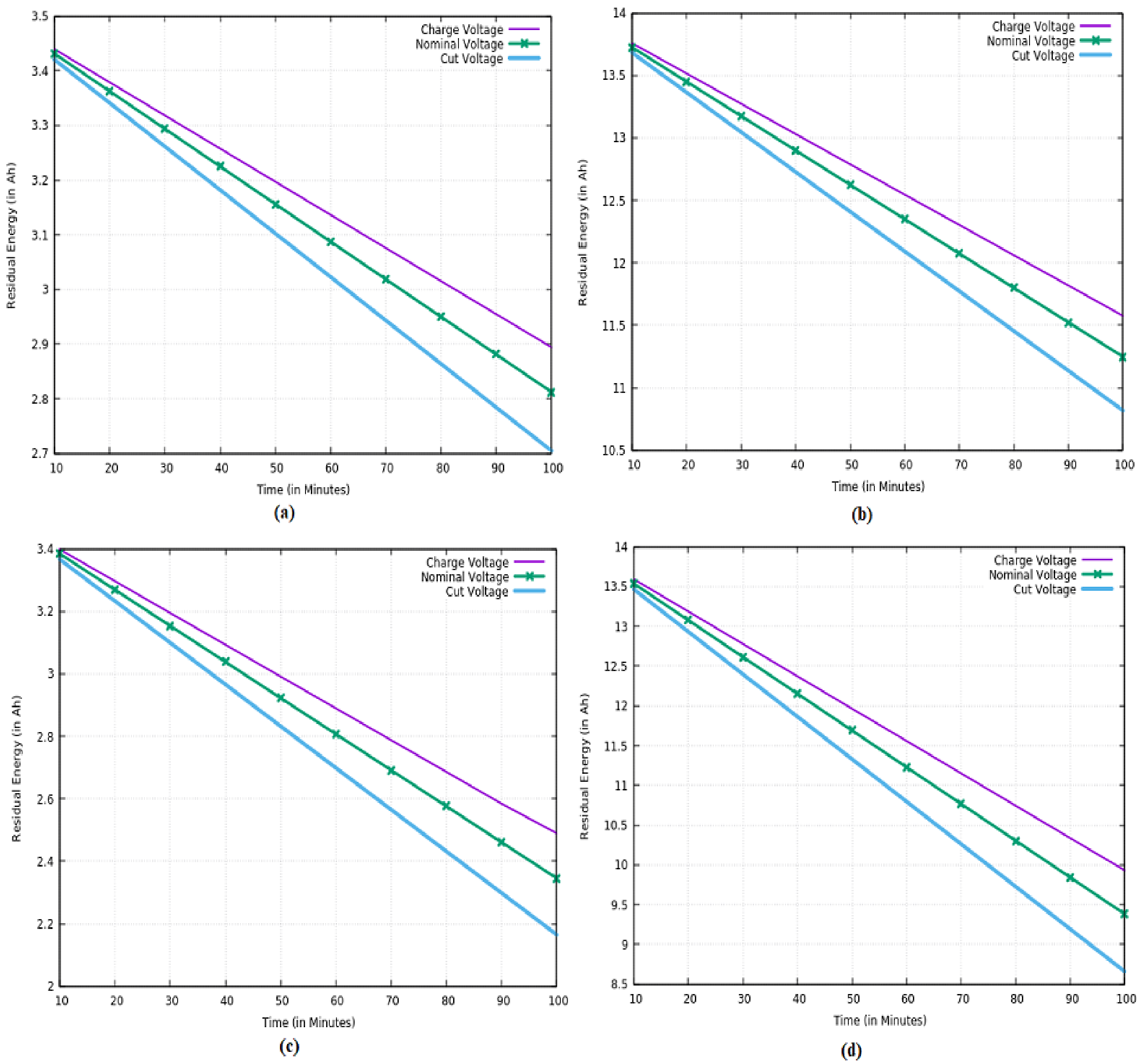


Figure 5.9. Variation of residual energy due to user context activity (a) For Calling for Type-I nodes. (b) For Calling for Type-II nodes. (c) For Messaging for Type-I nodes. (d) For Messaging for Type-II nodes.

Figure 5.10 illustrates the variation in residual energy for user context activity during Gaming App and OTT App. For Gaming App, the residual energy for Type-I and Type-II nodes was 2.95 Ah and 11.82 Ah at charge voltage, 2.88 Ah and 11.53 Ah at nominal voltage, and 2.78 Ah and 11.14 Ah at cut-off voltage. Similarly, for OTT App, the residual energy for Type-I and Type-II nodes was 3.04 Ah and 12.16 Ah at charge voltage, 2.97 Ah and 11.91 Ah at nominal voltage, and 2.89 Ah and 11.58 Ah at cut-off voltage.

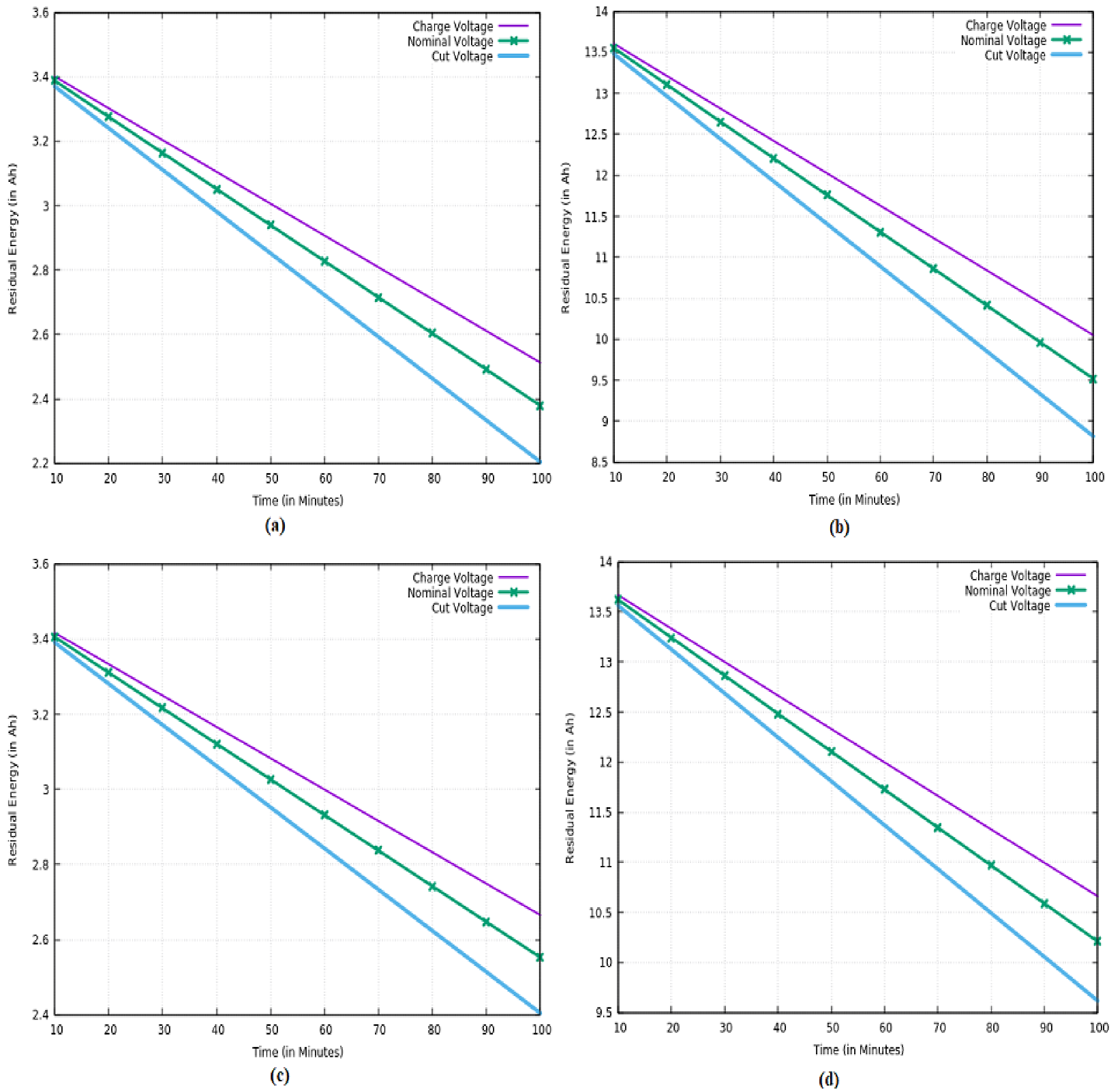


Figure 5.10. Variation of residual energy due to user context activity (a) For Gaming App for Type-I nodes. (b) For Gaming App for Type-II nodes. (c) For OTT App for Type-I nodes. (d) For OTT App for Type-II nodes.

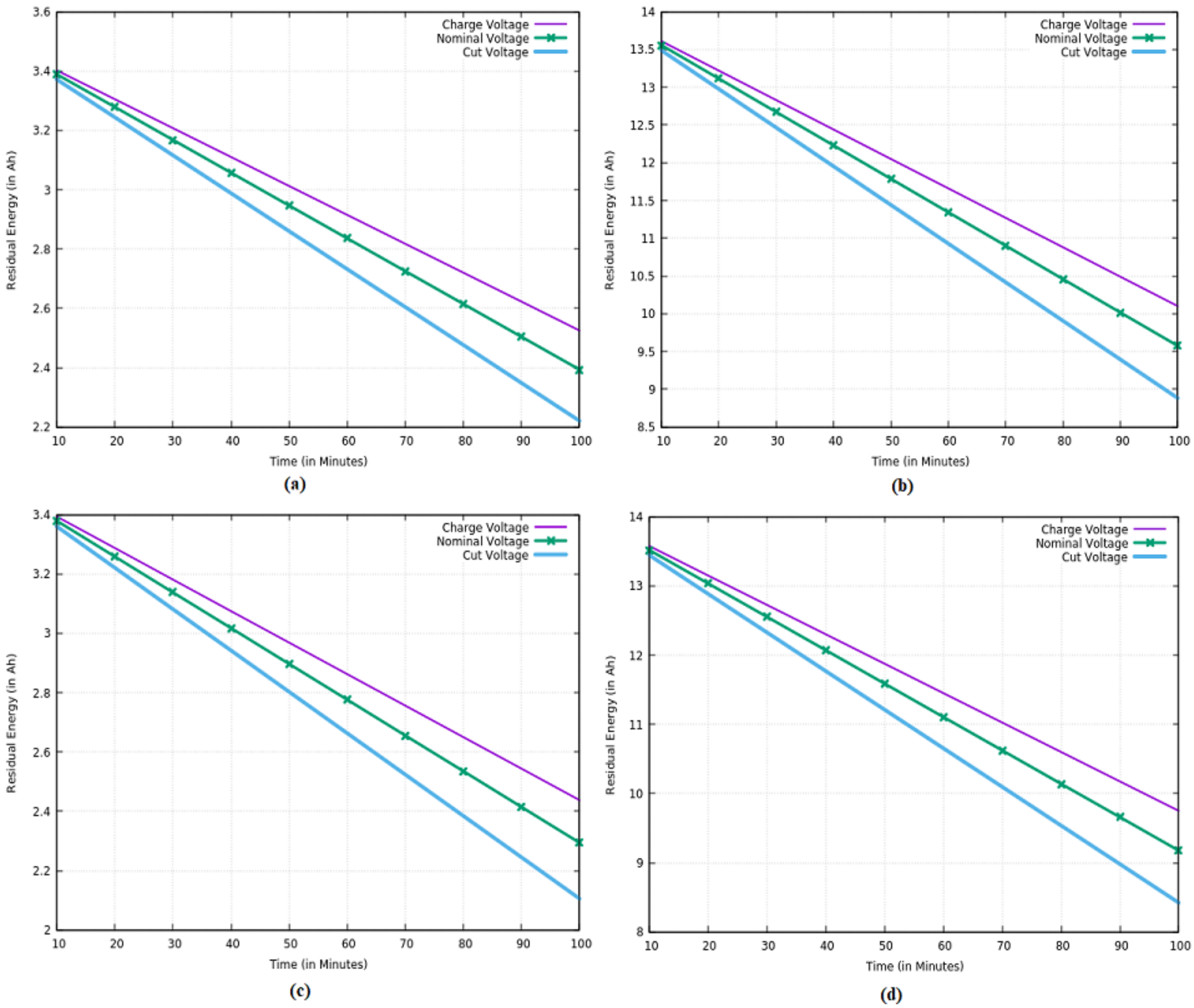


Figure 5.11. Variation of residual energy due to user context activity (a) For Conferencing App for Type-I nodes. (b) For Conferencing App for Type-II nodes. (c) For Editing App for Type-I nodes. (d) For Editing App for Type-II nodes.

Figure 5.11 illustrates the variation in residual energy for user context activity during Conferencing App and Editing App. For Conferencing App, the residual energy for Type-I and Type-II nodes was 2.96 Ah and 11.85 Ah at charge voltage, 2.89 Ah and 11.56 Ah at nominal voltage, and 2.79 Ah and 11.18 Ah at cut-off voltage. Similarly, for Editing App, the residual energy for Type-I and Type-II nodes was 2.91 Ah and11.66 Ah at charge voltage, 2.83 Ah and 11.34 Ah at nominal voltage, and 2.73 Ah and 10.93 Ah at cut-off voltage.

Figure 5.12(a) and Figure 5.12(b) illustrates the variation in residual energy for user context activity during Browsing. The average residual energy was 2.78 Ah and 11.14 Ah at charge voltage, 2.68 Ah and 10.75 Ah at nominal voltage, and 2.56 Ah and 10.25 Ah at cut-off voltage. Similarly, Figure 5.12(c) and Figure 5.12(d) illustrates the cumulative residual energy for user context activity for Type-I and Type-II nodes. The cumulative residual energy for Type-I and Type-II nodes was 38.50534046 Ah and 34.25 Ah at charge voltage, 37.59 Ah and 33.28 Ah at nominal voltage, and 36.43 Ah and 32.12 Ah at cut-off voltage.

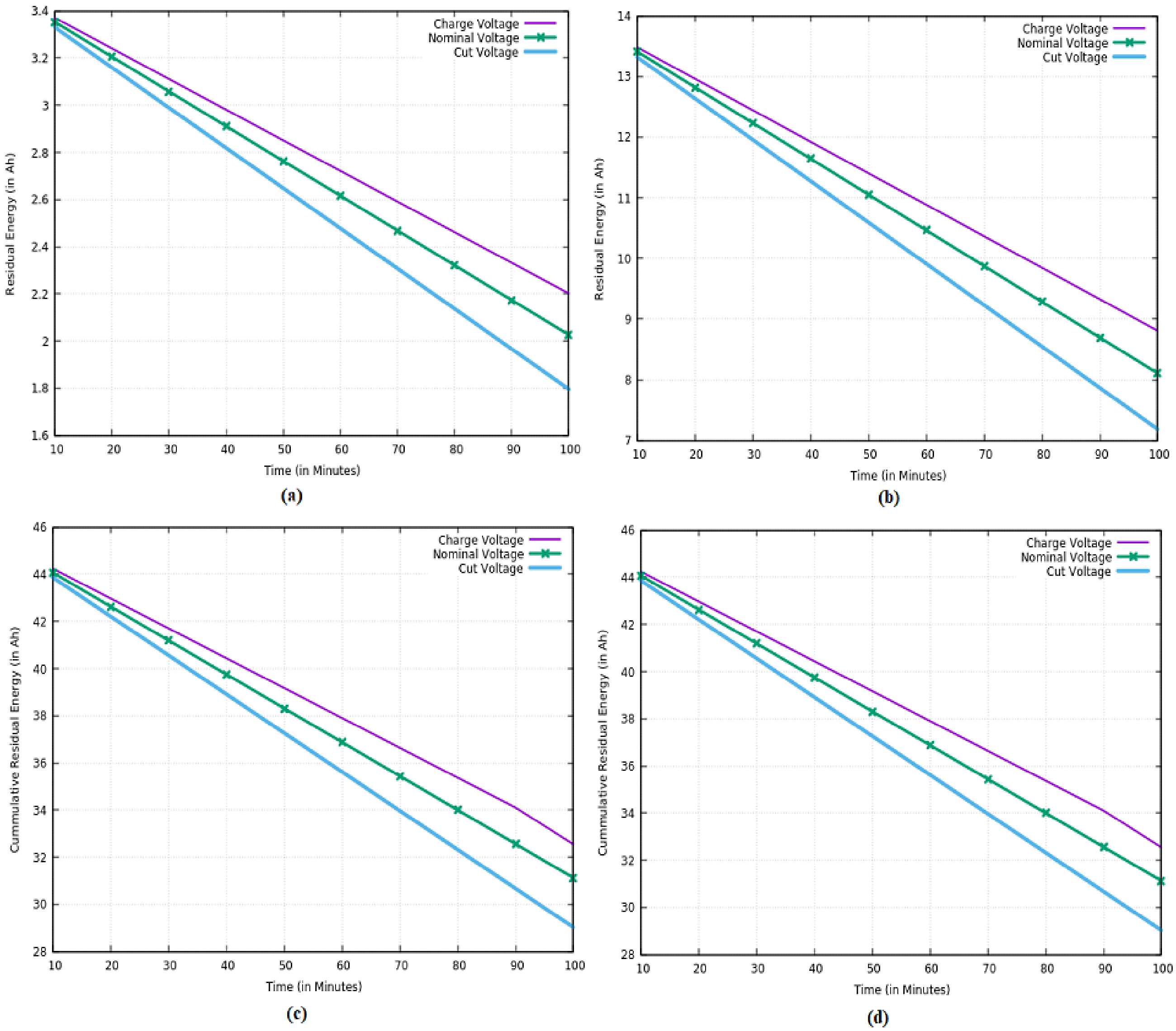


Figure 5.12. Variation of residual energy due to user context activity (a) For Browsing for Type-I nodes. (b) For Browsing for Type-II nodes. (c) Cumulative residual energy for Type-I nodes. (d) Cumulative residual energy for Type-II nodes.

Figure 5.13(a) and Figure 5.13(b) illustrates throughput for user context activity for Type-I and Type-II nodes. The average throughput was 176.729 Kbps and 364.97 Kbps at charge voltage, 150.489 Kbps and 338.73 Kbps at nominal voltage, and 137.369 Kbps and 325.61 Kbps at cut-off voltage. Similarly, Figure 5.13(c) and Figure 5.13(d) illustrates the average PDR for user context activity for Type-I and Type-II nodes. The average PDR for Type-I and Type-II nodes was 0.63 and 0.73 at charge voltage, 0.50 and 0.70 at nominal voltage, and 0.37 and 0.65 at cut-off voltage.

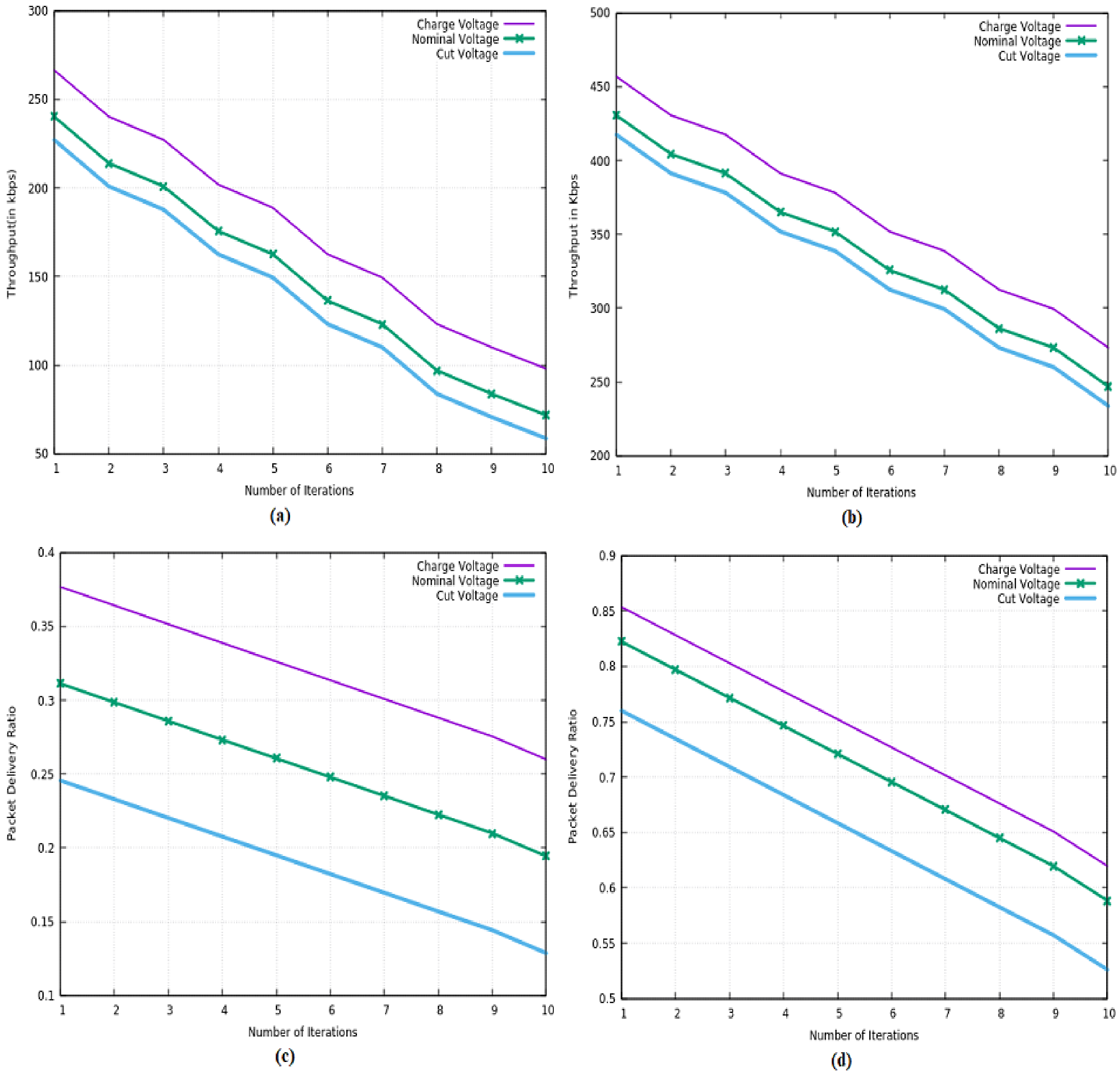


Figure 5.13. Network Performance analysis due to user context activity (a) Throughput for Type-I nodes. (b) Throughput for Type-II nodes. (c) PDR for Type-I nodes. (d) PDR for Type-II nodes.

5.2 DISCUSSIONS

- The power consumption du2e to user context activities increased and the residual energy decreased with every iteration for both Type-I and Type-II nodes. However Type-II nodes consumed more power than Type-I nodes which was found to be maximum at charge voltage and minimum at cutoff voltage.
- Similarly, the cumulative power consumption increased whereas the cumulative residual energy decreased with every iteration for both type of nodes. However it was comparatively more in Type-II nodes as compared to Type-I nodes and was found maximum at charge voltage and minimum at cut-off voltage for both Type- I and Type-II nodes.

- The throughput decreased with every iteration for both Type-I and Type- II nodes as the power consumption of nodes increased due to increase in user context activities. However, it was comparatively more in Type-II nodes than in Type-I nodes and found to be maximum at charge voltage but minimum at cutoff voltage.
- The PDR decreased with every iteration for both Type-I and Type-II nodes as the power consumption increased due to increase in user context activities. However, the PDR was comparatively more in Type-II nodes than in Type-I nodes. The PDR was highest at charge voltage comparatively lower at nominal voltage and lowest at cut-off voltage.

6. CONCLUSION

In the proposed methodology, comparative analysis of various user context activities over the power consumption of wireless nodes was performed. Various user context activities considered during the study included Bluetooth transfers, file transfers, browsing, calling, messaging, E-Commerce Apps OTT platforms, banking Apps, Conferencing Apps, and Editing Apps etc. The power consumption due to these Apps was calculated through Battery-Guru Android application. Power consumption due to these user activities was calculated during handover scenario for Type-I and Type-II nodes at three different voltage levels: charge voltage, nominal voltage, and cut-off voltage. Simulation results showed that power consumption of nodes increased with increase in the user context activities which was minimum at charge voltage, comparatively more at nominal voltage and maximum at cutoff voltage for Type-I and Type-II nodes. However, the power consumption was found to be comparatively more for Type-II nodes as compared to Type-I nodes. Moreover, throughput and PDR decreased as the power consumption increased. And was found to be maximum at charge voltage, comparatively lower for nominal voltage and minimum at cut-off voltage. Simulation results showed that Type-II nodes outperformed Type-I nodes in terms of throughput and PDR. This study analyzed the cumulative effect of various user activities over power consumption and performance of wireless networks and therefore can provide a robust framework for devising context aware energy efficient networking protocols to achieve sustainability in New Generation Networks(NGNs)

REFERENCES

1. Gupta,V., Bonde,P. "Handover Techniques in New Generation Wireless Networks." In Smart Computing and Informatics, pp. 127-138, 2018.
2. Gupta,V., Bonde,P. "Energy-Efficient Mechanisms for Next-Generation Green Networks." In Recent Findings in Intelligent Computing Techniques, pp. 415-423, 2018.
3. Zhang , D., Huang, H., Lai, C.F., Liang, X., Zou , Q., Guo, M. : Survey on context-awareness in ubiquitous media. In Multimed Tools Appl (2013) 67:179–211. Springer Science+Business Media, LLC 2011.
4. Nazir Malik, N., Mahmud, U.: Future Challenges in Context- Aware Computing. In IADIS International Conference, 2007.
5. Charith Perera, C., Zaslavsky, A., Christen,P., Georgakopoulos, D. : Context Aware Computing for The Internet of Things: A Survey. In IEEE Communications and Survey Tutorials.2013.
6. Hong, J., Suh, E., Kim, S. : Context-aware systems: A literature review and classification. In Expert Systems with Applications 36 (2009) 8509–8522. Elsevier 2008.
7. Bellavista, P., Corradi, A., Fanelli, M., Foschini, L. : A Survey of Context Data Distribution for Mobile Ubiquitous Systems. ACM Surveys, March 2013.
8. Lockhart, J.W., Pulickal , T., Weiss, G.M. : Applications of Mobile Activity Recognition. In UbiComp'12, September 5-8, 2012. ACM 2012.
9. Eiman Kanjo, E., Husain, L., Chamberlain, A. : Emotions in context: examining pervasive affective sensing systems, applications, and analyses. In Pers Ubiquit Comput (2015) 19:1197–1212. Springer 2015.

10. Hegering,H.G., Kupper, A. : Management Challenges of Context-Aware Services in Ubiquitous Environments. In 14th IFIP/IEEE International Workshop on Distributed Systems: Operations and Management, DSOM 2003.

11. Korpipaa, P., Mantyjarvi, J., Kela, J., Keranen, H., Malm, E.J. : Managing Context Information in Mobile Devices. Pervasive Computing, IEEE CS and IEEE ComSoc, 2003.

12. Mougy, A., Mouftah, H. : On Resource Management and Context-Awareness in LTE-Based Networks for Public Safety. In 13th Annual IEEE Workshop on Wireless Local Networks 2013. IEEE 2013.

13. Meng, Y., Jiang, C., Xu, L., Ren, Y., : User Association in Heterogeneous Networks: A Social Interaction Approach. In IEEE Transactions on Vehicular Technology. 2015

14. . Orlandi,B., Bizouarn, E.,Taburet,F., Scahill,F., Lafragette,J., Evenden,R., Ringland, S., Johnson,S., Melia,T.,Twell,T., Mghazli, Y.: Improving the Customer Experience for Heterogeneous Wireless Access. Alcatel-Lucent.2011.

15. Ali, Z., Baldo, N., Bafalluy, J.M., Giupponi, L. : Machine Learning Based Handover Management for Improved QoE in LTE. IEEE/IFIP Network Operations and Management Symposium (NOMS 2016). 2016.

16. Sarma,A., Chakraborty,S.,Nandi,S.: Deciding Handover Points Based on Context-Aware Load Balancing in a WiFi-WiMAX Heterogeneous Network Environment.In IEEE Transactions On Vehicular Technology, Vol. 65, No. 1, January 2016.

17. Cherkaoui, E., Agoulmine, N. : Context-aware Mobility Management with WiFi/3G Offloading for eHealth WBANs. In IEEE 16th International Conference on e-Health Networking, Applications and Services (Healthcom), 2014.

18. Lijuan, L., Tingjie, L.V., Xia, C.: Network Selection Based on Context-Awareness Services. In ICT Industry Convergence, China Communications, December 2013

19. Sarma,A., Chakraborty,S.,Nandi,S.: Context Aware Handover Management: Sustaining QoS and QoE in a Public IEEE 802.11e Hotspot. In IEEE Transactions On Network And Service Management, Vol. 11, No. 4, December 2014.

20. She, C.,Yang, C.: Context Aware Energy Efficient Optimization for Video On-demand Service over Wireless Networks. In IEEE/CIC ICCC 2015 Symposium on Communication and Control Theory. 2015

21. Ylianttila, M., Makela, J., Pahlavan, K.: Analysis of handoff in a location-aware vertical multi-access network. In Computer Networks 47 (2005) 185–201. Elsevier 2004.

22. Pawar, P., Beijnum, B.J., Sinderen,M., Aggarwal, A.,Maret, P., Clercq, F.: Performance evaluation of the context-aware handover mechanismfor the nomadic mobile services in remote patient monitoring. In Computer Communications 31 (2008) 3831–3842. Elsevier 2008.

23. TalebiFard, P, Leung, V.C.M. : A Dynamic Context-Aware Access Network Selection for Handover in Heterogeneous Network Environments. In IEEE, The Mobility Management in the Networks of the Future World (MobiWorld) Workshop, 2011.

24. Manzoor,A., Truong, H., Dustdar, S.: Quality Aware Context Information Aggregation System for Pervasive Environments. In International Conference on Advanced Information Networking and Applications Workshops. IEEE 2009.

25. Miettinen, M., Heuser, S., Kronz, W,. Sadeghi, A., Asokan, N. : ConXsense – Automated Context Classification for Context-Aware Access Control. In ACM 2014.

26. Lin,Y., Huang-Fu,C., Alrajeh, N. : Predicting Human Movement Based on Telecom's Handoff in Mobile Networks. In IEEE Transactions on Mobile Computing., Vol. 12, No. 6, June 2013.

27. Niutanen, J.,: Improving Usability and Context Awareness over Fifth Generation (5G) Wireless Networks. In Proceedings of 5th conference of Fruct Association, 2013

28. Ali, Mumtaz & Muhammad, Arshad & Uddin, Ijaz & Binsawad, Muhammad & Sawad, Abdullah & Sohaib, Osama. (2024). Efficient context-aware computing: a systematic model for dynamic working memory updates in context-aware computing. PeerJ Computer Science. 10. e2129. 10.7717/peerj-cs.2129.