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Energy Efficient Developments of Smartphone Environment and Cellular Network – Opportunities and Challenges

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Abstract — Smartphones bring people into different level of computing and life style but all the features and computing abilities of smartphone is entirely rely upon battery backup. Short of power backup directly distresses user experience and it leverages new energy efficient findings. Over the past ten years, plethora of finding is carried out related to energy optimization and conservation developments of smartphone and mobile communication and this changes the entire perspective of the platform. This paper tries to fetch such a trend setting outcomes from the legendary researchers, compares them and provides evidence of the fact. This review of literature covers a wide range of the study regarding 3G/4G network communication, Smartphone Apps performance and usage patterns and highlights their research proposals, solutions, architectures and results regarding to the energy efficiency in smartphone and cellular network. This literature study may offer many research directions to the upcoming researchers.

Keywords— Traffic Aware Optimization, Radio Signal Strength, Screen Off, Smartphone, Energy Efficiency, Cellular Network, Mobile Computing.

I. INTRODUCTION

There is no doubt that, smartphones contribute a significant role in our daily life, but the device is a battery dependent and its entire durability and progress are based on power backup and network coverage. From the beginning, the research findings are the key to enhance the user experience and would be the core of the smartphone evolution. According to the energy optimisation of 3G/4G networks and smartphone environment, there are plenty of authors have presented their outstanding work. Among that, few authors like Feng Qian, Niranjana Balasubramaniam have contributed exceptionally well towards energy cutting of smartphone. Feng Qian and morley Mao and their team have contributed a phenomenal work towards the mitigation of energy in smartphone zone state. This team has proposed variety of architectures, methods and real-time traces relating to the energy efficient exploration and this team holds the highest number of citation of their papers. Likewise, Hari Balakrishnan, Niranjana Balasubramanian, and their team initiated the research to fine-tune and optimize the radio resources of 3G networks. This kind of studies impulses 3GPP to update the working principles of RRC the state machine and stimulate to invent fast Dormancy feature in next releases of UMTS. In the meanwhile, several researchers have found numerous issues regarding energy loss and network performance of the smartphone.

The structure of this review is as follows. Section II highlights the scope of the review importance of the study. Section III discusses adaptive radio network performance traffic optimization in that section the review focus particularly on RRC Inactivity timers, fast dormancy, and traffic aware scheduling mechanism. After that, it discusses mobile internet optimization and optimal multimedia services as well. Characterizing of smartphone application performance and measurements are given in section IV. Then the paper has discussed the user behavior on smartphone usage in section V. In section VI, the review presents attention-grabbing factor that how smartphone screen and radio signal influence energy consumption. Finally, the paper points out the potential understanding of this survey and future research directions in section VII.

II. SCOPE OF THE REVIEW

The objective of this review is to explore the real fact of the research behind the energy efficiency. This study intentionally leaves out all work that focuses on the energy efficiency of network infrastructures, such as cellular network base stations, channel encoding and compression and operating system infrastructure such as memory optimisation and CPU optimisation etc. The proposed review is much keened to emphasize the working principles of RRC, mobile application performance, user behavior patterns and communication comportment. Several kinds of research evident wireless components are energy-hungry part of the smartphone, particularly cellular radio. The researchers like Feng Qian [66], Niranjana Balasubramanian [1], Xiaomeng chen [65], Shuo Deng [27], Yeseong Kim [18], le wang [31] etc. have contributed exceptional work towards the energy optimization on the mobile phone. This paper covers all aspects of research in and around their work (i.e Cellular network performance and optimisation, Screen Statuses). The second portion covers mobile Apps behavior, particularly how they behaved in screen-off mode. It intentionally leaves out the performance of foreground activities and its internal infrastructure.

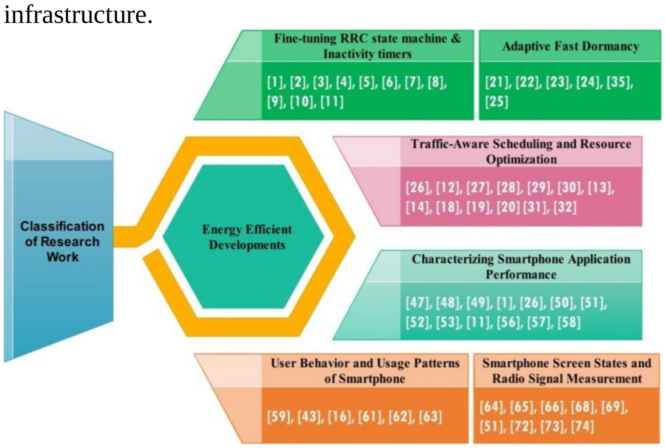

Figure 1. Classification of the Research Work

Finally, the review has moved to influence of cellular radio signal strength on smartphone energy through the measurement of received signal quality (Table 1). This study focuses out bearer setup, error detection and correction and power management.

Table 1. Classification of the Research Work

Research Topic	**Research Solutions**
Fine-tuning RRC state machine & Inactivity timers	[1], [2], [3], [4], [5],[6], [7], [8], [9], [10], [11]
Adaptive Fast Dormancy	[21], [22], [23], [24], [35], [25]
Traffic-Aware Scheduling and Resource Optimization	[26], [12], [27], [28], [29], [30], [13], [14], [18], [19], [20] [31], [32]
Characterizing Smartphone Application Performance	[47], [48], [49], [1], [26], [50], [51], [52], [53], [11], [56], [57], [58]
User Behavior and Usage Patterns of Smartphone	[59], [43], [16], [61], [62], [63]
Smartphone Screen States and Radio Signal Measurement	[64], [65], [66], [68], [69], [51], [72], [73], [74]

III. Adaptive Radio Network Performance Traffic Optimization

Many have networked applications that run in the background on a mobile device incur significant energy drains when using the cellular radio interface for communication. This is mainly due to the radio tail, where the cellular radio remains in a high energy state for a particular inactive time after each communication spurt. In order to cut down energy consumption, many works have proposed techniques to measure and optimize network performance and energy efficiency based on traffic pattern, network elements and user behaviors etc.

A. Fine-tuning of RRC State Machine and Inactivity Timers

Inactivity timers, that verify the tail times, are the foremost necessary parameters in cellular radio resource management. Radio Resource Control (RRC) tail [1] is critical and important for cellular networks to forestall frequent state promotions (resource allocation), which might cause intolerably long delays for the UE, as well as additional process overheads for the radio access network [2, 3]. Trendy cellular carriers use a static and conservative setting of the tail time within the order of the many seconds, and previous studies have revealed this tail time to be the root cause of energy and radio resource inefficiencies in both 3G and 4G [1, 4, 5, 6]. The impact of inactivity timers on the UMTS network capability [6] additionally the UE energy consumption [7] has also been studied.

Proceeding of the above research, Pekka and Barbuzzi [8] have projected a novel scientific method to measure and observe RRC state transitions. This method has introduced a measurement technique referred to as 3GTT (3G) that is used to induce RRC State transition and network parameters of UMTS primarily based networks. Through this research, the author reveals that the state of the UE directly depends on the user traffic and in addition the characteristic of generated and received traffic of the UE is directly coupled with RRC state transition on the UTRAN. Henry et al [9] attempt to explore the energy consumption of always-on application in WCDMA networks. This paper reveals that keep-alive messages of always-on applications extremely interact with RRC and this process results in the intolerably short battery lifetime of mobile phones. This paper starts a discussion with numerous states of RRC protocol i.e. CELL_DCH, CELL_FACH and CELL_PCH [9] and every state consumes completely different operating power on UE.

Perricci et al [10] and Metri et al [11] reveal the elaborate experimental result regarding the energy consumption of smartphone elements. This research tells wireless technologies to act as primary energy consumers than the display and CPU however this research was conducted on Symbian OS. Niranjana Balasubramanian et al [1] have proposed a measurement-driven model for the energy consumption of network activities (3G, GSM, and WiFi) and developed energy efficient protocol referred to as TailEnder to attenuate the accumulative network energy consumption. The protocol mitigates energy loss by 32%, 52% and 40% for email applications, news feeds, and web search respectively. The author gets the protocol results through simulation and therefore the mechanism of prefetching relies on the third party data and browsing logs. Therefore the TailEnder scheduler could be a smart idea and implementation is required.

B. Adaptive Fast Dormancy

Intelligently switching RRC states between active and idle will cut back bandwidth value and network congestion if tuned and optimized properly. Otherwise, it will cause serious performance degradation and inessential signaling traffic. The authors Feng Qian et al [21], Pavan K. Athivarapu et al [22], Yuheng Huang et al [23] and Jacques Bou Abdo et al [24] have proposed a comparable prediction algorithms called Tail Optimisation Protocol, RadioJackey, Adaptive Fast Dormancy (AFD) controller and user-level dynamic decision algorithm respectively to cut tail time through invoke fast dormancy effectively. Each of those methods has used a distinct approach to mitigate tail time. However, these researches are related in predicting network idle time depends on the application traffic generated on UE. At identical time, fast dormancy is not invoked if the predicted idle period is smaller than a predefined threshold called tail threshold to prevent unnecessary state promotions. The value of the tail threshold and other TOP parameters are carefully tune based on empirically measuring traces collected from a large UMTS carrier [21]. TOP, AFD, and RadioJackey even introduces a novel coordination and machine learning algorithm to determine RRC state transitions by the aggregated traffic of individual applications running on a UE. More significantly, all of those models need not modify network architecture and it will be adapted to any or all smartphone environment with minimum changes. The experimental results supported real traces show that with reasonable prediction accuracy, TOP saves the radio energy (up to 17%) and radio resources (up to 14%) by reducing tail times by up to 60% [21]. Even RadioJockey achieves 20% - 40% energy savings with negligible increase in signaling overhead [22].

The author [35] fine tunes tail time and fast dormancy by altering the user firewall settings to attain energy efficiency. The simulation result indicates that employing a short static timeout would possibly decrease the wasted energy by 73% and only cause 22% increase within the amount of signaling required to make state transitions from PCH to DCH. Guangtao Xue [25] determines a scheme called SmartCut that effectively mitigates the tail effect of radio usage in 3G networks with a bit side-effect of user experience.

C. Traffic-Aware Scheduling and Resource Optimization

Feng Qian [26] has presented the first network-wide, large-scale investigation of a particular type of application traffic pattern called periodic transfers where a handset periodically exchanges some data to a remote server at every ‘t’ seconds [26]. In the beginning, the results that argue periodic transfers are predominant in today’s smartphone internet traffic. However, they are extremely resource-inefficient for both the network and UE even though they primarily generate very little traffic, this is somewhat crucial to the principles of energy conservation and network radio resource management policies. For instance, widespread smartphone applications such as Facebook, periodic transfers account for only 1.7% of the overall traffic volume but contribute to 30% of the total handset radio energy consumption [26]. This shows how the short burst influences radio energy.

Huang et al [12] have projected a practical system referred to as RadioProphet to dynamically de-allocate radio resource based on network idle time and user traffic log. This system runs on the UE and predicts the network idle time through online machine learning algorithm supported collects traces. The author achieves 59.1% radio energy saved on UE however it causes 91% further signaling overhead.

Shuo Deng et al [27] have initiated two distinct algorithm called MakeIdle and MakeActive to cut back radio energy by changing radio states dynamically based on perceptive network traffic. These two algorithms use statistical machine learning techniques (Bank of Expert) [28-29] to observe real-time network traffic pattern and predict the future traffic shape. According to this prediction the state transition can be forcefully invoked. This approach is well-suited to the emerging fast dormancy mechanism [30] that enables a radio to rapidly move between the Active and Idle states and the other way around (Fig 2). The most objective of this paper is to diminish the energy consumed by networked background applications on UE and it achieves energy efficiency between 51% and 66% for 3G and is 67% on LTE network.

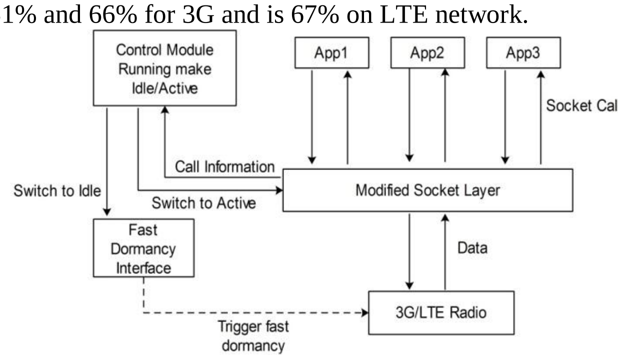

Figure 2. System Design [27]

Author [13] has introduced a design known as SALSA that is an optimal online algorithm to fine-tune energy_delay trade_off based on the link selection and it schedules the data transfer based on the traffic. The author achieves 10%-40% energy save through this architecture. The author [14] has projected a prediction and inference technique based on probing of user traffic and the algorithm systematically discovers the state transmission by strategically adjusting the packet dynamics. This paper has proposed two algorithms for inferring state promotion and demotions. The state promotions are happened based on traffic volume which is measured in RLC buffer and state demotions are happened based on inactivity timers [14]. The interesting result is by adjusting one inactivity timer by 3 seconds will cut back overall radio resource usage by 40% however it will increase 31% state promotions and network overhead. Owing to in-proper state promotion and demotion of RRC cause network in-efficiency and affect UE energy efficiency because of tail effect.

Yeseong Kim [18] has proposed an architecture known as personalized diapause (pD) that is monitor user network pattern and releases the radio resources using fast dormancy. This study has collected a huge range of network activity pattern from the user (such as browsing, email and social network) and predicts user-specific tail time behavior of each network transmission. The working principle of pD is chooses a candidate subintervals of the tail-time interval where a radio connection overhead is a smaller than a given threshold value and invokes the fast dormancy feature at a time point among the candidate subintervals where an energy saving is maximized [18]. Finally, the pD extracts the pattern information from the Apps call stack and predicts tail transmission patterns for every extracted network activity [18].

$$Pk = \frac{n_k}{\sum_{j=0}^{N} nj} \tag{1}$$

The prediction engine work based on the equation (1) and the algorithm (Algorithm 1) was introduced to predict next dormancy based on the network pattern.

Algorithm 1

// assumes the fast dormancy feature is invoked at b_i

$B \leftarrow 0$;

For each b_i in { $b_i, \ldots\ldots, b_N$ } do

If an IS occurs at b_j

Saving $\leftarrow$ (j-i) $\times$ $E_{subtail}$;

Penalty $\leftarrow$ ($j \neq N$) ? $E_{ohd} : 0$;

$\beta \leftarrow \beta + p_j \times (saving - penalty)$;

end

$q_i \leftarrow (i \neq 0)$? $\sum_{k=0}^{i=1} pk : 0$;

$G_i \leftarrow (1-q_i) \times \beta$;

pD can save the radio energy consumption on average by 23 percent over when no fast dormancy feature is used with less than 10 percent reconnection increase.

Mohamed Oulmahdi [19] has conducted an elaborate measurement study relating to the impact of keep-alive messages and has proposed a method called sender-based keep-alive mechanism for minimize the energy of radio communication. Unlike traditional keep-alive mechanism, it suppresses the server request and formulates the client side request at a specific time interval. R R Kar and S S Nayak [20] have introduced a strategy of efficient adaptive channel allocation scheme that controls and manages the guard channel to scale back the handoff blocking rate and new call blocking rate. The paper determines the guard channel allocation based on traffic and user behavior in varied period of time. The authors counsel that, if the user traffic is low, the allocation of guard channel ought to be less variety. If the new call rejection rate and handoff dropping rate is higher than the threshold value, the allocation of guard channel ought to be a high range.

Le wang, Anna and Evgeny Belyaev [31] have explored the power consumption variation of the 3G mobile phone through fixed rate data transmission. The finding of the study of the energy consumption is directly related to packet size and time interval. The measurement result shows the faster transmission and receiving interval cause most no of the peak of power consumption than the maximum transmission interval. The experiment has been conducted by traffic generator because of the measurement have to be compelled to transfer fixed data at a fixed interval. In this paper [32], the author describes ARO tool that profiles all the activities of Apps from a higher layer to lower layer, that’s why it's known as Cross_layer approach. The finding of the tool is to prove small bursts are extremely influence RRC states and radio energy. This paper proposes an RRC state inference algorithm to fine-tune RRC inactivity and achieve significant energy saving [32].

IV. CHARACTERIZING SMARTPHONE APPLICATION PERFORMANCE

Mobile app performance has become crucial one that has received a good deal of interest among the researchers, and existing works have examined several aspects of Apps performance together with papers on Accurate Active Performance Analysis [42], Application usage [43], Cellular data drain [44], Apps behavior [45], energy efficiency when downloading and rendering web content in the foreground [33], and the impact of user behavior [59]. This section focuses on background activities of smartphone applications and its energy consumption [15].

Numerous works have conjointly examined various aspects of background network activities particularly Aucinas et al. examined smartphone energy efficiency through in-lab experiments with a number of major apps which maintain a continuous online presence [47]. The background traffic not only transferred when the phone is in Idle mode even it can also occur when the phone is active. The study [1, 26, 49] discourse the periodic transfer of short network burst and Tamer [50] confirms the mobile apps are woken up frequently to update themselves and demonstrates method to interposing the Apps wakeups in the background [15].

Work by Chen et al [51] presents a large-scale user study of how users use their phones and how that interacts with app battery consumption and developed a hybrid power model for estimating energy drain of the hardware components and apps and services running on the smartphones [51]. Their study is complementary, covering all sources of energy consumption and trends across classes of devices, whereas the main focus on examining the role of background network transfers. The analysis of traces collected on 1520 Galaxy S3 and S4 devices within the wild covering 800 apps gained much insight on energy drain across devices (users), device components, apps, and multiple technology and app evolutions. The measurement results that over 92.6% of the apps have a median power draw between 200-400 mA. However, the Apps such that Speedtest.net, Deezer Music, BBC iPlayer, Kill Shot have average power draw between 600 mA and 832mA. One Wi-Fi test app and 2 music apps consume 66.8%, 46.5% and 49.7% of total energy on network respectively. On the other hand, the gaming Apps consumes 39.8% energy on CPU [51].

Continue from the research [11, 55, 56], Ding Li confirms cellular network is a high energy consumer than other smartphone hardware components through broad measurement study. Another interesting fact is about 61% of the apps energy usage is spent in their IDLE states and the energy consumption of network element such that HTTP, Socket and Webkit are 80%, 0.27%, 10%, respectively. Moreover, 75% of the applications spend more than 89% of their network energy in HTTP [52]. This result points out the HTTP request is that the dominating network energy consumption. Ville Kononen et al [53] have projected a method to mitigate background energy of Apps supported the stimulating time in the UE. The author has introduced two types of time thresholds to freeze the Apps activities for a while, one is maintaining a minimum and maximum value of time, second is about only maximum time. The result shows up to 50% of energy gain is achieved by this method.

Grace et al [11] have argued the results of two broad case studies relating to the influence of background application and network type in energy consumption. The study has been conducted on two platforms android and iPhone. The analysis shows 3G networks consume additional energy than Wi-Fi once transferring data. The author suggests some strategies to optimize energy consumption on the device. Sai Suren Kumar Kasiredd [56] presents an analytical report that is energy consumption of the device components varies among the OS. During this analysis, four smartphone models have been used, among the four; two are java based and two are the android based phone. The attention-grabbing finding is android platform consume more energy than another platform.

Ahmed Abdelmotalib et al [57] confirms the periodic background traffic heavily impact UE energy. The research [58] examined the energy consumption of state machine directly relating to application payload. It confirms the Always-On Apps generate small network payload and leverage the RRC state machine to switch among them. The paper suggests the parameters to modify the RRC inactivity time and eliminate its energy loss.

V. User Behavior and Usage Patterns of Smartphone

A plethora of studies have focused on understanding the pattern of user behavior from different perspectives. Among them, studies of user behavior on smartphone have yielded insights into different entities in the mobile computing community. Accordingly, understanding the user behavior on mobile apps is critical because every user has diverse mental attitude.

Hossein Falaki et al [59] argues that their findings that the mean number of interactions per day for a user varies from 10 to 200; the mean interaction length varies from 10 to 250 seconds; the number of applications used varies from 10 to 90; and the mean amount of traffic per day varies from 1 to 1000 MB, of which 10 to 90% is exchanged during interactive use. Even games and maps applications more often tend to have longer interactions [59]. Another finding of the study is that many short interactions likely drain more energy than a few long interactions, as those interactions probably change the state of the relevant components such as network data modules, CPU, or memory. The variation in the interaction with the smartphone causes variation in the energy consumption as well as in the data usage [59]. The author [43] underlines while in travelling several social networking and games apps are more frequently used. Mobility affects connectivity and performance so that the developers and designers ought to consider techniques to compensate signal strength variations.

Heikkinen and Nurminen [16] have enquired consumer aspiration regarding the energy consumption of smartphones and its services. They have conducted a scientific study through questionnaires among Finnish university students. The theme of the study is to spot the followings

- Energy awareness
- Energy –driven customization
- Energy as decision criteria

The study has been conducted among a hundred and fifty students both undergraduate and postgraduate students. The questionnaires are categorized into phone setting and service properties, battery life, battery recharging, energy consumption and impact of battery charge level to user behavior [43]. The findings of the study are 81% of the respondents prefer to get automatic features to optimize the energy consumption. 73% of the consumers offer high priority to battery backup once purchase smartphones. 83% - 87% customers prefer to receive a lot of energy awareness information's from applications and operators [16].

Nan E, Xiaoli Chu et al [61] have introduced a replacement statistical model to seek out the user traffic analysis that is time-varying and location varying within the populated area on weekdays and weekend. During this analysis collected vast no of real data from 1668 NodeB's and cells. The author continuously collects data regarding once in 15 minutes in 7 days. The result says that the users having a lot of knowledge transfers during office hours of weekdays than the weekend. The paper uses PDF (probability density function) and histograms to search out the throughput of the given time during a given day.

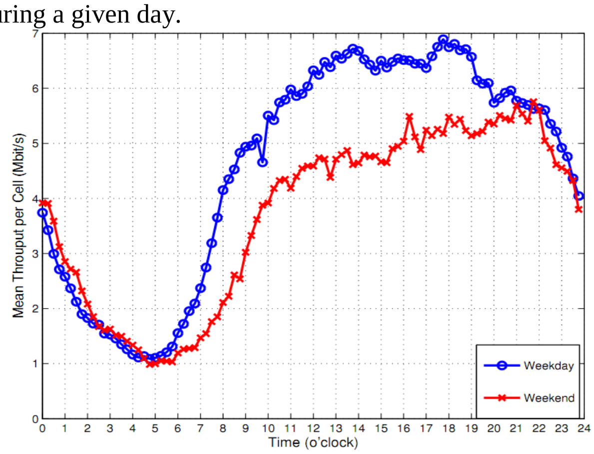

Figure 3. Usage comparison of Week days and Week end [61]

The mean throughput of the weekdays has a minimum value at 5:00 and the maximum value at 17:45 per cell. For weekends, the minimum mean throughput per cell occurs at 5:00 while the maximum occurs at 22:00. The week day's throughput from 6:00 to 21:00 is much higher than weekend throughput (Fig 3).
Ahmad Rahmati at al [62] have bestowed their elaborate study relating to Human-Battery Interaction on Mobile Phones. During this survey, the author provides qualitative and quantitative evidence of user interfaces has led to under-utilized power-saving settings, under-utilized battery energy, and dissatisfied users.
The author has conducted an in depth paper-based survey relating to phone power characteristics and user anxiety relating to battery time period. The study has been conducted among 350 respondents from postgraduate, undergraduate and school students. The respondents are categorized into two.

1. People who frequently charge their phone whenever convenient, in spite of the charge level.
2. People who charge their phone based on charge level feedback from the phones battery interface.

The findings of the analysis are given below:
Mobile phone users often have inadequate knowledge of the power characteristics of mobile phones and their features.

- Battery indicators are inaccurate; many of them provide insufficient information.
- Many users are unaware of the mere existence of power-saving settings
- Power-saving settings remain largely unutilized.
- Current UIs for power-saving settings are inadequate

The attention-grabbing finding that the user been asked whether or not they have taken any steps to extend battery life, 16 % have responded they stop using some features; 19% have responded they put off their phones; 13% have bought a brand new battery; 20%, probably Type-A users, claimed that they had never taken any steps.
This research [63] has determined a new Context-Aware Battery Management (CABMAN) architecture for mobile devices that are predicting the battery life and next charging opportunity. The CABMAN predicts the subsequent.

- Time for next charging opportunity
- How much calls can be made until the next charging
- The battery duration based on the application usage.

To evaluate the performance of the charging opportunity predictor and decision time predictor the paper has used an oversized trace of measurements of real users captured in MIT's Reality Mining project. The author predicts succeeding charging station based on the cell location that is, the algorithm marked certain cells for charging point based on the usage pattern. The travel distance and time may be predicted based on the present cell and nearest charging cell. The call time can be predicted based on call patterns and this can be enhanced by viewing weekdays and weekend days separately since call behavior is likely to differ in that time [63].
The prediction results with charging opportunity prediction exhibiting a median error of 12 minutes, battery life prediction having average errors of between 4 and 12 minutes depending on the device used [63].

VI. Smartphone Screen States and Radio Signal Measurement

According to Google Statistics, smartphones are the backbone of our daily media interactions with the highest proportion, 38%, as compared to different devices similar to tablets, and PC. The statistics additionally show that 54% and 33% of the entire operation time of smartphones are spent in communication and entertainment, respectively. The average interaction time on the smartphone screen is 17 min (minutes) per day [64]. Another study reveals on the average, the users spend around 2.56 hours per day actively interacting with their phones; the 10th percentile and 90th percentile screen-on time are 0.84 and 4.62 hours, respectively. Inevitably, the statistics are extremely variable depending on the country and also the users. This makes "one-model-fits-all" almost impossible [65].
Feng Qian, Oliver Spatscheck and their team have done such a remarkable work relating to screen off energy optimization and therefore the team has proposed plethora of measurement results and arose variety of research issues likewise. This research [66] has introduced two optimization techniques such as fast dormancy and batching to optimize screen off energy usage. This analysis proves the background activities of apps consume 41.2% energy in screen off state.
The research [68] has introduced a technique for intelligently manage traffic using Network Socket Request Manager

(NSRM). This methodology controls the application background traffic through controlling the data connection. The author [69] has extended the [68] work and has projected a method referred to as ExpCO2 to control the Apps background network activity of a smartphone through dynamic cellular data-enabled and data-disabled durations at the screen-OFF state. The author conducts a broad survey of 5 users and 3 phone types so far, and has found the most energy gain ratio of data ON/OFF is 1 min/29 min respectively. This ratio saves the energy up to 34% without loss of user experience.

The work [65] has proposed a system called HUSH (screen-off optimizer) that monitors the metrics online and automatically identifies and suppresses background activities during screen-off periods that are not supposed to affect the user experience. In doing so, the proposed HUSH saves screen-off energy of smartphones by 15.7% on the average whereas incurring marginal impact on the user experience with the apps [65]. The author presents most significant data through survey report that is on the average 45.9% of the overall energy drain in a day occurs during screen-off periods. To extend the previous work the author [51] developed a hybrid utilization-based and FSM-based model that accurately estimates energy breakdown among activities and phone components without ever-changing the android framework or rooting the phone [51].

Aaron Schulman et al [72] have a different perspective approach and has proposed novel design of energy efficient cellular network. The research exploits the signal strength encompasses a direct impact on radio energy consumption that may be a major factor of overall energy consumption on mobile devices like smartphones and introduces an algorithm for scheduled radio communication. The author proves that there is a correlation between lower signal, lower bit rate and higher transmission time. Through this algorithm, the research achieves energy savings up to 60% minutes for the streaming applications and energy savings of up to 10% for the e-mail sync application.

The study [73] presents a unique technique known as LoadSense for a cellular client to obtain a measure of the cellular load, locally and passively, that permits the client to determine the perfect times for communication once available throughput to the client is probably going to be high [73]. There has been a lot of research on quantifying the energy costs, both because of transmission and reception [72] and signaling-induced radio-tail periods [21]. A key determinant of throughput is that the link quality, which is quantified by the strength of the base station's pilot signal, as recorded at the receiver [73]. Once the UE is close to the cell tower, the higher the pilot power it sees and also the higher the modulation rate that may be used. On the other hand, the farther the device is from the tower, the lower the pilot power it measures and also the lower the usable modulation rate.

$$Power\ Ratio = \frac{Pilot\ Power}{Total\ Raw\ Power}$$

In LTE, the particular parameters of the above equation correspond to the pilot power and the power ratio is called Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ), respectively. Based on this power ratio the author present their final contribution is the Peek-n-Sneak protocol, which allows cellular clients to "peek" into the channel cheaply and "sneak" in with their communication when the conditions are suitable, i.e., when high throughput is predicted [73].

Ning Ding [74] has conducted a wide measurement regarding the impact of wireless signal strength on energy consumption. The study proves low signal strength leverage extra energy for data transfer due to including rate adaptation, power control, link layer re-transmissions and TCP retransmissions. According to 3G network, the increased energy on data transfer and RRC state demotion when the RSSI drops from -85dBm to -105dBm dominates the extra energy consumption, resulting in 52.0% more energy for 100 KB download with 30ms server RTT [74]. The author has developed a new system-call-driven power model to delaying of background traffic can reduce the total energy consumption of data communication by up to 23.7%and 21.5% under Wi-Fi and 3G, respectively, assuming a maximum delay of 12 hours [74].

VII. CONCLUSION

According to the previous literature study, regulating RRC state machine is that the traditional technique to optimize radio energy on UE. The researchers have given productive results but because of the frequent update of cellular architecture, these results could not create that much impact and their research works have become mirage. Even those types of proposals produced simulation-based results and extremely difficult to test in the real-time scenario so that the planned work entirely deviates from those works. Regarding fast dormancy, most of the results are based on inference and these strategies are tested in a simulated environment also but produced exceptional outputs. According to the traffic aware researches, previous works are terribly productive and generic however our planned works go beyond with good results. Mobile internet optimization, multimedia services, and user behavior provides essential information and research directions and also the author thinks about this results and statistics to the design of proposed architecture. The work [66, 51, 65] has achieved maximum result regarding screen off findings but those strategies are not generic and it has to modify the core of the mobile operating system. The work [68, 69] can be generic one but it does not consider signal quality when enabling the Data_on schedule. The research [72] has done an identical analysis but the traveling path and traveling time could be a factor to decide the prediction accuracy. The work [73, 74] has focused another dimension of energy savings but they take into account network factors only.

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