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Greener and Smarter Phones for Future Cities: Characterizing the Impact of GPS Signal Strength on Power Consumption

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ABSTRACT Smart cities appear as the next stage of urbanization aiming to not only exploit physical and digital infrastructure for urban development but also the intellectual and social capital as its core ingredient for urbanization. Smart cities harness the power of data from sensors in order to understand and manage city systems. The most important of these sensing devices are smartphones as they provide the most important means to connect the smart city systems with its citizens, allowing personalization n and cocreation. The battery lifetime of smartphones is one of the most important parameters in achieving good user experience for the device. Therefore, the management and the optimization of handheld device applications in relation to their power consumption are an important area of research. This paper investigates the relationship between the energy consumption of a localization application and the strength of the global positioning system (GPS) signal. This is an important focus, because location-based applications are among the top power-hungry applications. We conduct experiments on two android location-based applications, one developed by us, and the other one, off the shelf. We use the results from the measurements of the two applications to derive a mathematical model that describes the power consumption in smartphones in terms of SNR and the time to first fix. The results from this study show that higher SNR values of GPS signals do consume less energy, while low GPS signals causing faster battery drain (38% as compared with 13%). To the best of our knowledge, this is the first study that provides a quantitative understanding of how the poor strength (SNR) of satellite signals will cause relatively higher power drain from a smartphone's battery.

INDEX TERMS Green mobile computing, energy efficiency, smart cities, smart phones, signal strength, power model.

I. INTRODUCTION

Smart cities appear as the next stage of urbanization, subsequent to knowledge-based economy, digital economy, and intelligent economy. Smart cities aim to not only exploit physical and digital infrastructure for urban development but also the intellectual and social capital as its core ingredient for urbanization. A city can be defined as "smart" when "investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance" [1]. Smart cities can also be seen also as "converged ubiquitous infrastructures" and "complex systems of systems".

A number of trends have contributed to the development of smart cities. These include a pressing need for environmental sustainability, and peoples' increasing demands for personalization and mobility. Several 'smart cities' around the world are being built from scratch while many of the modern cities are gradually moving towards becoming 'smart'. We are now used to of Google-Maps, which enables us to navigate to our destination avoiding congested routes based on real-time traffic data. Mobile applications such as Citymapper [2] allows us to travel through the city using public and other transport modes providing near real-time information. Many other developments such as Internet of things (IoT) for smart cities [3], semantic web for smart cities data [4], smart emergency management systems [5], autonomic transportation systems [6], traffic-aware street lighting scheme [7], planning and land administration [8], strategies for smart cities [9], privacy-aware participation [10], crimesourcing [11], community resilience [12], smart grid and metering, and many other proposals [6], [13]–[22] are shaping our move towards the smart cities era.

At the heart of smart cities is the concept of harnessing the power of data from sensors to understand and manage city systems. Sensors therefore are playing a critical role in enabling smart cities technologies and systems. Sensors provide the pulse of the city helping it to apply some control measures before a major breakdown happens. The city pulse, enabled by sensors and streams of information, also facilitates the citizens with a high quality of life.

Perhaps the most important of these sensing devices are smartphones (and other personal devices such as tablets). This is mainly because smartphones provide the most important means to connect the smart city systems with its citizens, allowing personalization and co-creation. Smart phones currently have 14 or more sensors to monitor the environment and provide various facilities to the user [23]. These include the accelerometer, gyroscope, magnetometer, proximity sensor, light sensor, barometer, thermometer, air humidity sensor, pedometer, heart rate monitor, fingerprint sensors, harmful radiation detector, hall sensor, gesture sensor, microphone and the cameras. It is expected that gas sensors will also be integrated into smartphones enabling indoor air quality monitoring [24]. Smartphones also provide powerful computing abilities and are being used in plethora of applications and use cases, such as smart car parks [25], accelerators for ecommerce, fitness and health [26], [27], connected cars, participatory smart citizenship, social behavior change interventions [28], and many of the smart city applications that we have mentioned above. Moreover, while the UN statistics about doubling of the global urban population by 2050 is causing nightmares for city managers and politicians, this increasing number, considering the decreasing smartphone prices, is likely to provide fine grained, dense information about the city to the public and other stakeholders (due to the increasing smartphone ownership among urban populations).

The discussions given above suggest that the popularity and applications of smart mobile devices, and hence the industry, will continue to grow at extraordinary rates. Different studies also show that in the near future handheld devices will be much more marketable for web browsing and other functionalities compared to the personal computers. The contemporary smartphones are increasingly considered as handheld computers rather than as phones. This is in part due to their powerful on-board computing capability, large memories and screens, and open operating systems that support application development [29]. Unfortunately, as a result, applications that are designed for mobile devices are getting computationally heavier and their complexity is on the rise. The common applications that are run on mobile devices include voice and video based applications (skype, whatsapp, etc.), video games, navigation applications, internet access and web browsing applications.

Many applications for mobile devices make use of the user's location information to provide various services and enhance user experience. These applications include, among others, mapping applications (e.g. Google maps), chatting applications (e.g. tango, WhatsApp, and Viber), and social network applications (e.g. Facebook, and twitter). For example, travel and navigation related applications make use of the users' locations to guide them throughout their journeys; informing them, based on their preferences, of the best routes and means to get to their destinations. Similarly, user's location can be used by an application to provide them with a nearest point of interest or the physical proximity of their friends. There are multiples technologies to find user's location using smartphones. These include GPS, its variants, and WiFi.

Mobile devices support portability by using rechargeable batteries. Batteries obviously need to be very small in size to keep the handheld devices light and small. A Mobile device consumes energy from its battery as long as the device is on and running. The energy drawn from a battery depends on the number of applications and their energy requirements. Some applications are much heavier than others in terms of their energy requirements. Applications that require identification of user location to provide their services are among the top power-hungry applications. This is because of the fact that localization technologies, particularly GPS (Global Positioning System), have high processing and communication costs. A continuous use of localization applications typically leads to energy drain from a battery in few hours. The battery lifetime for handheld devices is one of the most important parameters in achieving good user experience for the device. For these reasons, management and optimization of handheld applications in relation to their power consumption is a highly researched topic in mobile handheld computing.

In this paper, we assert that GPS signal strength not only affects location sensing performance but also the actual consumed power from a smartphone battery. Specifically, we investigate and analyze the quantitative relationship between the SNR (Signal-to-Noise-Ratio) of the GPS satellite and the amount of power consumption while using a localization service.

We develop an Android mobile application for the power consumption related measurements. We use the results from the measurements of our developed application, as well as from an off the shelf application, to derive a mathematical model that describes the power consumption in smartphones in terms of SNR and the TTFF. The results from the study show that higher SNR values of GPS signals do consume less energy while low GPS signals causing faster battery drains. To the best of our knowledge, this is the first study that provides a quantitative understanding of how the poor strength (SNR) of satellite signals will cause relatively higher power drain from a smartphone's battery.

The rest of this paper is organized as follows: section II presents the motivation behind this research followed by the literature review in section III. Section IV gives related background, and section V presents the trace analysis. Our mathematical model is presented in Section VI. We conclude this paper in section VII.

II. MOTIVATIONS

Nowadays smartphone users search for power plugs instead of network connectivity, because of the gap between smartphone development and battery enhancement and because they use their smartphones almost for everything, so battery is a critical challenge for this technology. Many emerging applications for different services are implemented for smartphones. Several smartphone new applications demand location positioning systems to provide location based services. Many methodologies are used to provide such services but GPS stays the best among its alternatives even it is the hungriest for power because of its accuracy.

In our work, we try to highlight the problem of GPS component high power consumption by concentrating on GPS satellites signal strength effect on battery energy drain in order to help in saving energy in the component level so user's high expectations can be met. To proof our concept we used one android location based application of the applications available on Google play store and we built another one and named it ''GPS SNR''. Our application uses GPS hardware as a location provider that monitors GPS satellites and requests location coordinates update every 20 seconds.

In this part, we motivate our work by highlighting some results. Let us meditate our major experiment that is running one LBA (location based application) on LG Nexus 4 smartphone for 1 hour indoor and outdoor. In one hour, running the LBA we choose from Google play store indoor where satellites SNR didn't exceed 25 (which is considered as bad SNR) consumes 21% of the mobile battery and such high power consumption can bring down the battery in like 5 hours for continues GPS sensing. Running the same application outdoor where satellites SNR gets stronger and reaches 41 (which is considered as good SNR) consumes only 13% of the mobile battery. From this experiment, we can simply observe that power consumed under good satellites signal strength can be reduced to about 38% as compared to power consumed under bad satellites signal strength.

III. LITERATURE REVIEW

Lately, smartphones spreads widely and rapidly for many uses, at the same time using periods of smartphones is decreasing continuously as screens get wider and bigger and loads get heavier. Many researches showed how energy consumption in smartphones battery can be much efficient and surveyed several techniques and solutions to reduce energy consumed from battery and increase its lifetime without affecting any functionalities in order to optimize smartphone's architecture and software such as what is proposed in [30] that finds out how system's components waste power for unnecessary usage.

Different studies have analyzed energy drain from smartphone battery and many researches have been made about what apps and services drain energy from batteries the most and different works measured weak and strong WiFi and 3G and other wireless interfaces signal strength impact on a battery power consumption. Researchers in [31] performed a measurement study for WiFi and 3G signal strength experimented by 3785 users used their smartphone daily for periods between 1 and 19 months. This research showed that variations of WiFi and 3G signal strength cause variations of power consumption rates from smartphone batteries by quantifying and breaking down the impact of poor WiFi and 3G signal strength on all relevant layers of the network stack. Authors of [32] established the relationship between power consumption and signal strength and they showed that energy cost of communicating is affected by cellular network signal strength. In other words, poor signal strength raises the energy cost of communicating and good signal strength reduces it. On the other side, they developed a track-based signal strength prediction and energy-aware scheduling algorithms. In [33], the authors analyzed energy consumed for different workloads in different components of WiFi based phones and measured the power draw of WiFi-based phones to increase slightly under poor signal strength, when dynamic power control is enabled. In [34], an in-depth study of power dissipation of smartphone components is performed and the researchers found that GSM dissipates 30% more energy when transferring at poor signal strength. Choi [31] studied the waste power from different smartphone components by setting different usage scenarios and analyzing each component behavior. Components such as CPU, LCD, GPS, WiFi, Bluetooth, etc. . . .

In our research, we focused on another source of power consuming sources for smartphone battery. We studied GPS satellites signal strength effect on the smartphone battery. All smartphones use different locating methods to estimate locations precisely to provide location based services. However, it is power hungry; GPS is the preferred positioning system because it is the most accurate among all the alternatives.

Our work is one of few measurement studies of GPS satellites signal strength effect on battery drain of smartphones but there are many researches provided location sensing frameworks that improve energy efficiency of location sensing. Authors of [35] considered the power starving location sensing process and succeeded to reduce GPS usage for location determination by up to 98% and to improve battery lifetime by to 75%. In [36] authors concentrated on the less accuracy issue of GPS in urban areas so they designed a rate-adaptive positioning system that uses different techniques to decide when to turn on GPS and when not and then evaluated their implemented system for different experiments on modern smartphone. Their experiments showed that battery lifetime is increased by the factor 3.8 comparative to it when GPS is always on. In research [26], GPS power model was described for the first time. They studied the effect of many GPS-related variables on power consumption such as number of satellites detected, and signal strength of each satellite while considering the state of GPS (active with many satellites available, active with few satellites available and sleep). Their study showed that energy drained for GPS depends strongly on weather GPS component is active or in sleep mode and it has little dependency on the number of satellites available or the signal strength. In our research, we are proving the opposite of this idea. We will show in measurements that GPS signal strength affects power consumption in smartphone battery.

IV. BACKGROUND

In this section, we review power states that smartphone experiences while sensing for GPS satellites signals to determine a specific location.

As smartphones commonly use rechargeable batteries for power supplying and batteries mostly take from one hour and a half to four hours to be recharged and ready to supply phones with demanded energy, discharge behavior and rates must be realized and analyzed in order to understand how each component consumes power and how it wastes power [37].

Each device has several power states and in each state different amounts of power is consumed. The main two states a smartphone experiences are idle state and productive state. In the idle state, a specific device requires minimal possible power. In the productive state many modes a smartphone experiences according to the workloads the device handles. Permanently after each workload and before getting back to the idle state, a device passes through a period during which it keeps consuming power in high rates [37]–[39].

We measured power states for GPS on LG Nexus 4 smartphone depending on the power model presented by Ning Ding in [40]. Figure 1 shows power states a user equipment (UE) experiences for GPS: (1) Inactive GPS power state: where GPS antenna is disabled and a device is not sensing using GPS for a specific location. In this state, GPS consumes no rower. After pressing the GPS button once to start sensing and according to our power model, the device moves to the next state which is (2) Fixing power state: the state in which GPS is activated and its antenna is enabled consuming specific amount of energy considering TTFF–the time required for finding InView satellites and deciding which are the InUse satellites and then starting to calculate the location coordinates- according to our Energy-TTFF relationship that we will describe latter in this paper. In this state, power consumption increases in a high rate and it takes like 20 seconds between each TTFF and another. (3) Working (sensing) power state: this state comes right after satellites acquisition where power consumption is measured according to our Energy-SNR relationship that is described latter.

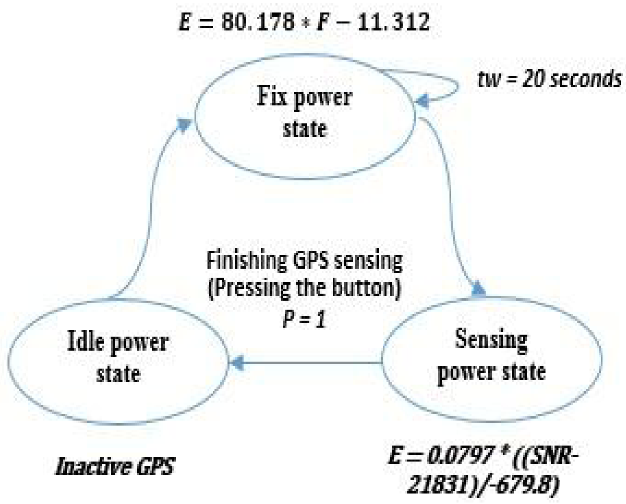

FIGURE 1. GPS power state machine for LG Nexus phone.

V. TRACE ANALYSIS

In this section, we present our experiments in details. We will talk about the two kinds of applications we used and the traces we have done to reach our goals.

A. TRACE COLLECTION/ENERGY IMPACT OF WEAK AND STRONG GPS SATELLITES SIGNAL STRENGTH DEPENDING ON BATTERY CHARGE LEVEL

We depend here only on battery charge level that we read from the smartphone in order to realize the changes that occur on the battery charge level while locating the device using GPS satellites under weak and good signal strengths.

We used a location based application LBA that is available on Google play store. This application uses the user current location to find and track people nearby. We ran this LBA on fully charged LG Nexus 4 smartphone and observed its battery for one hour and we recorded the battery every six minutes. We repeat this experiment inside where GPS satellites signal strength is weaker (less than 25) and outside where it is stronger (around 42). Figure 2 presents the results of this experiment. This figure simply shows that when running the same location based application for one hour inside with weaker GPS satellites signal strength (less than 25) and outside with stronger GPS satellites signal strength (around 42), battery consumption rates is differing according to the device location (inside or outside). When running the application inside, battery level decreases from 100% to 79%, in other words, battery charge decreases by 21%, and when running the location based application outside, battery level decreases from 100% to 87%, in other words, battery charge decreases by 13%. Consequently, running this LBA under good satellite SNR reduces power consumed by like 38% compared against power consumed under bad satellite SNR.

In addition to using Location Based Application from Google play store, we build our android application and named it GPS SNR. Our application uses GPS hardware as

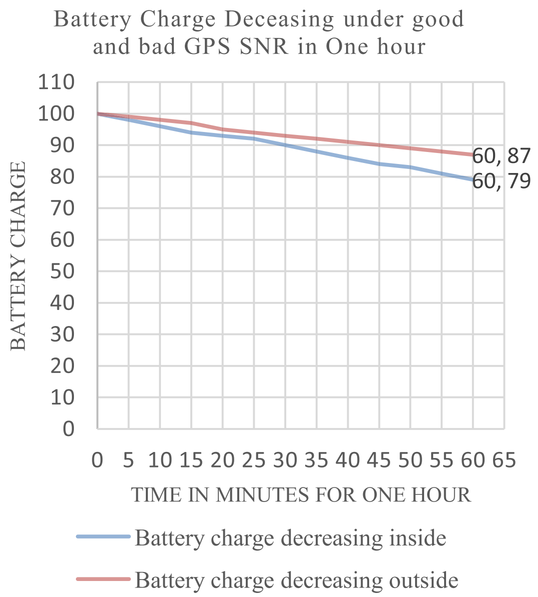

FIGURE 2. **Energy impact of weak and strong GPS satellites signal strength depending on reading battery charge level.**

a location provider and it monitors GPS satellites and request coordinates update every 20 seconds and Figure 3 shows the interface of GPS SNR.

FIGURE 3. **GPS SNR interface.**

As shown in Figure 3, our application reports any location latitude and longitude every 20 seconds and shows the number of InView and InUse satellites for a specific point. InView satellites are all satellites that cover device's location and InUse satellites are satellites that are used for location determination.

We ran GPS SNR for 30 minutes and recorded the decreasing of battery charge every 5 minutes. Just like the previous experiment, we ran this application indoors and outdoors. In the next two tables (1 and 2), we present the results.

TABLE 1. **GPS SNR results indoors.**

Min	# Sat. InView	# Sat. InUse	SNR for InUse	Battery level (%)
0	16	7	2 5 0	100
5	16	5	2 1 2	98
10	16	5	1 4 0	97
15	16	2	1 1 0	96
20	15	4	1 3 0	95
25	16	3	1 2 0	94
30	15	2	0 2 0	93
				Total=7%

SNR Color Legend			
SNR	0-10	11-20	21-30
Color			

From Table 1, we can see that satellite's SNR mainly was at the first and second range and rarely reach the third range, which can be considered as a bad SNR. Under these bad SNR under these bad SNR and after 30 minutes the consumed power by this application is 7% of the battery.

From Table 2, we see that satellite's SNR become stronger and enters a new range (31-40), which can be considered as good SNR. The overall battery consumption when running the application for 30 minutes under these circumstances was 4%.

B. TRACE COLLECTION/ENERGY IMPACT OF WEAK AND STRONG GPS SATELLITES SIGNAL STRENGTH USING MONSOON

The process of finding mobile location coordination – as per any application request – consists of the following steps:

1- Finding the InView satellites.
2- Determine which of the InView satellites can be used to find the current location (InUse satellites).
3- Start calculating the location coordination.

These steps take variable time that is called **Time To First Fix TTFF**.

As in the previous section, we noticed that there is a relationship between the amount of the consumed power and

TABLE 2. GPS SNR results outdoors.

Min	# Sat. InView	# Sat. InUse	SNR for InUse	Battery level (%)
0	18	8	1 1 5 1	100
5	16	4	0 0 4 0	99
10	16	4	0 1 2 1	99
15	16	7	0 1 4 2	98
20	18	5	0 0 2 3	98
25	18	7	0 0 4 3	97
30	18	8	1 3 3 1	96
				Total=4%

SNR Color Legend				
SNR	0 - 10	11 - 20	21 - 30	31 - 40
Color				

the signal strength of satellite used in location determination. However, the question is how the SNR affects the process of location finding and hence the consumed power?

To answer the previous question we have used a power monitor tool called Monsoon, this tool monitor the power consumed from the mobile device battery. Therefore, we connect the monsoon to Samsung S4 mobile and monitor the power consumption while running our GPS SNR application indoor and outdoor.

Following are 2 screen shuts that are taken while running Monsoon to monitor power consumed from battery while running GPS SNR application.

Indoor (inside 2 floors building with 25 cm thickness walls): figure 4 shows that there are three fixing periods that are directly proportional to SNR. In the first fix period, fixing time (TTFF) was 12619 milliseconds, and there were 3 satellites that have SNR in the range of 21-30 and 3 satellites that have SNR in the range of 11-20 and both are considered weak.

In the second fix period, fixing time (TTFF) became longer (63620 milliseconds) because SNR got weaker as just two satellites have SNR in the 21-30 range. In the third fix period, fixing time (TTFF) is the shortest (9605 milliseconds) as there are 4 satellites of SNR in the range 21-30.

Outdoor: figure 5 shows that there are three fix periods having almost similar and short fixing times (TTFF) (around 2600 milliseconds) as when using GPS outdoor, satellites SNR becomes stronger and can reach 40 or more.

From both figures 4 and 5, we can see that during fixing time (TTFF) the device consumes more power, so that, longer fixing time (TTFF) means more power consumption. Thus the answer to the question of what is the relation between satellite SNR, fixing time (TTFF), and the power consumption is; weaker satellite SNR leads to longer fixing time (TTFF) and hence more consumed power, and vice versa.

VI. MATHEMATICAL MODEL

To make our experiment's findings clearer we represent it using mathematical equations. This process done in three phases: A) SNR and TTFF relationship. B) TTFF and Consumed Energy relationship. Depending on the previous two phases, we found the third relationship C) TTFF and Consumed Energy relationship.

A. SNR AND TTFF RELATIONSHIP

We ran GPS SNR application in different places and recorded satellites SNRs and fix-time needed to find the location. This time we concentrate on how to describe and formulate the relationship between the SNR and TTFF. However, we could formulate the relationship between TTFF and lowest signal strength among all the InUse satellites signal strengths, and we could formulate the relationship between TTFF and highest signal strength among all the InUse satellites signal strengths.

Following are two figures for the both previously mentioned relationships. In figure 6 we formulate the relationship between TTFF and lowest signal strength among all the InUse Satellites signal strengths using liner regression modeling, and we got the following equation:

$$SNR = -679.8 * TTFF + 21831$$

Where SNR is minimum GPS satellite signal strength and TTFF is Time To First Fix. In figure 7 we formulate the relationship between TTFF and highest signal strength among all the InUse Satellites signal strengths using liner regression modeling, and we got the following equation:

$$SNR = -561.01 * TTFF + 22756$$

Where SNR is maximum GPS satellite signal strength and TTFF is Time To First Fix. Both following figures (figure 6 and figure 7) support our assumption of higher GPS satellites SNR needs less time and lower GPS satellites SNR needs more time as actual and linear regression curves in both figures decreasing. In other words, as sensing for location is carried out by high signal strength of GPS satellites, TTFF will be as short as possible and thus power consumption will be minimized.

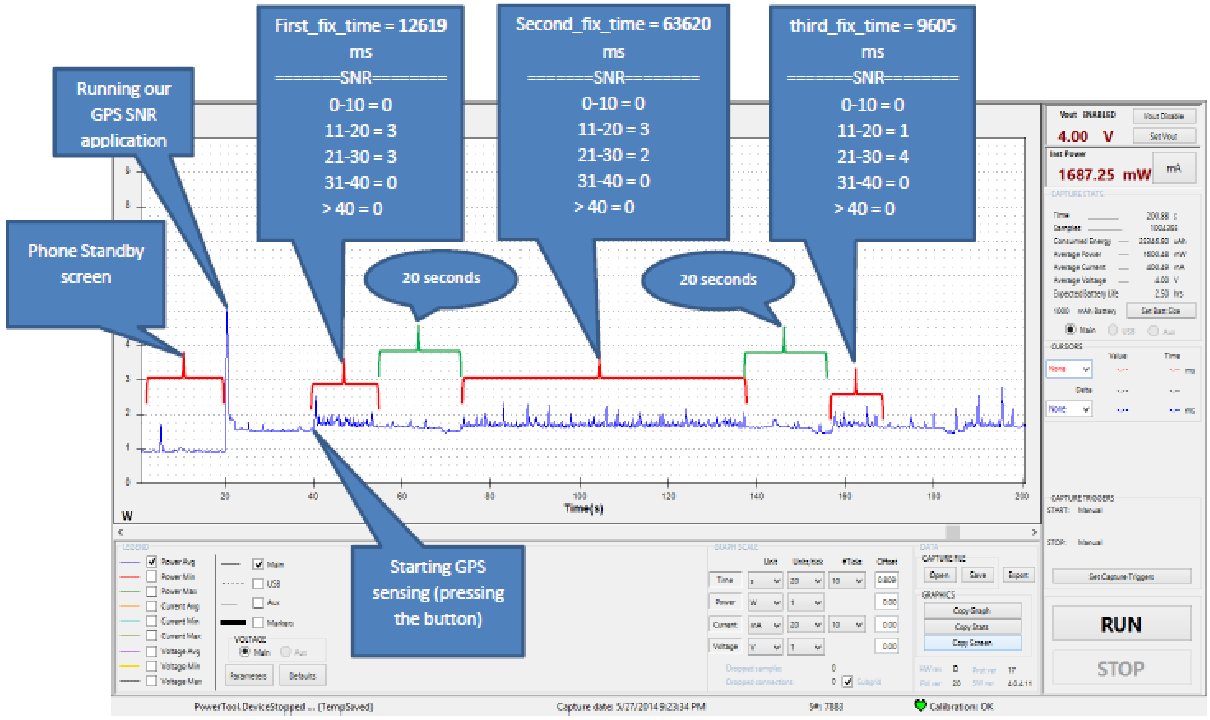

FIGURE 4. Monsoon screen shut of power consumption rates while running GPS SNR application indoor.

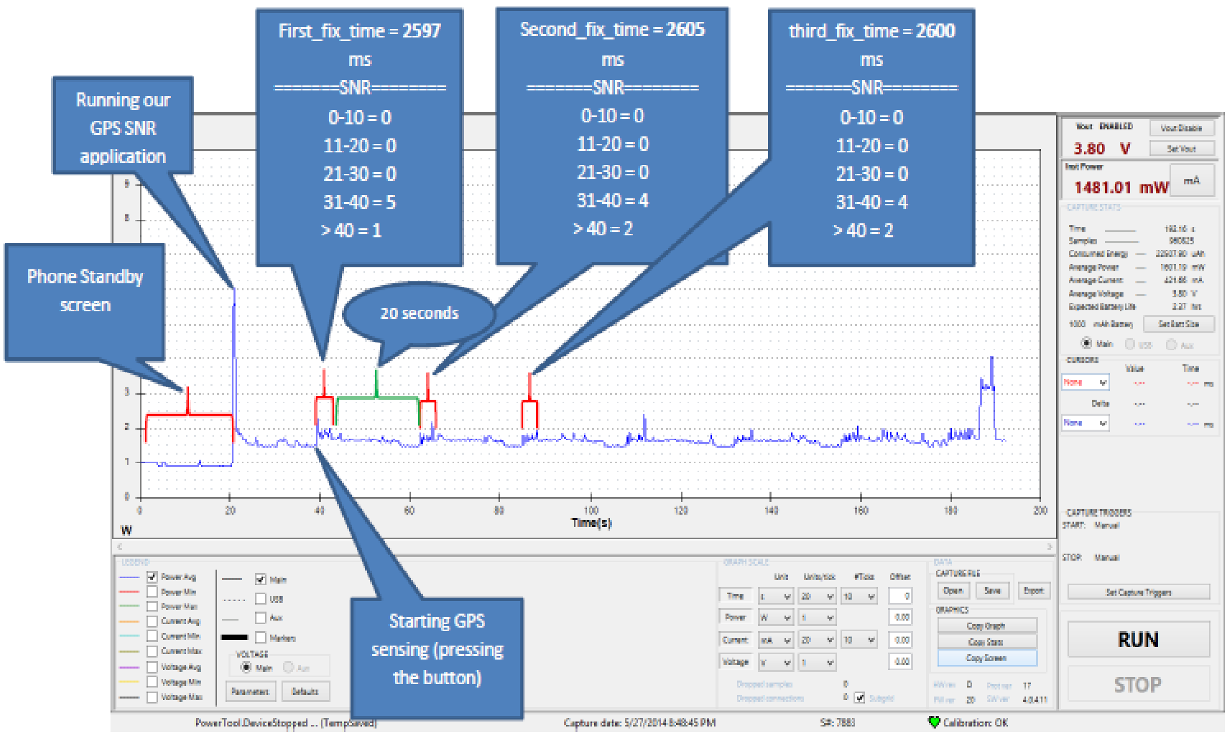

FIGURE 5. Monsoon screen shut of power consumption rates while running GPS SNR application outdoor.

B. TTFF AND CONSUMED ENERGY RELATIONSHIP

We also ran GPS SNR application while connecting the mobile device to the monsoon, but this time we recorded the value of TTFF and the consumed energy during this time. Then we formulate the relationship between the both variables using liner regression modeling, and we got the

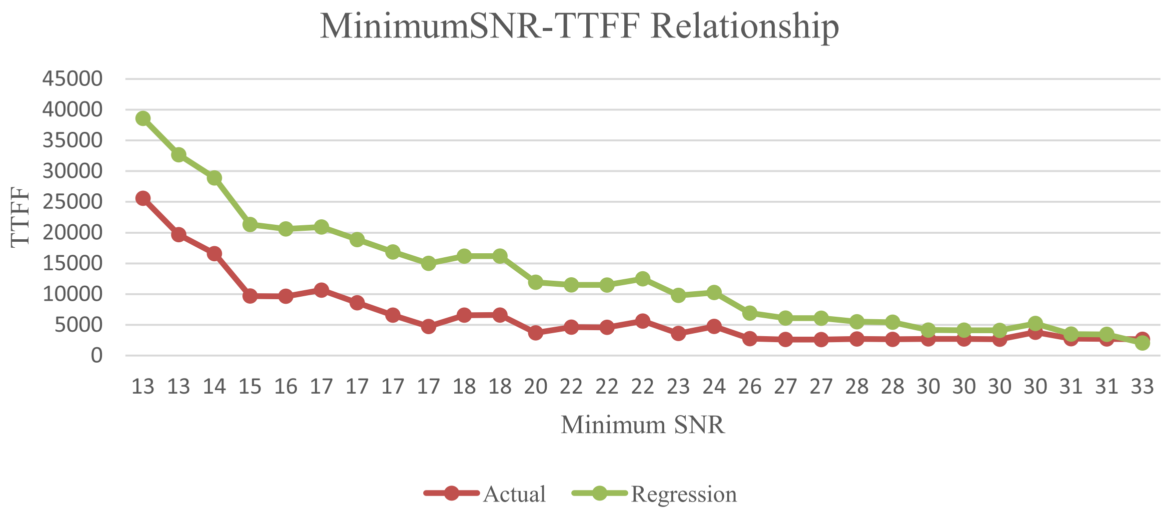

FIGURE 6. **Minimum SNR-TTFF relationship.**

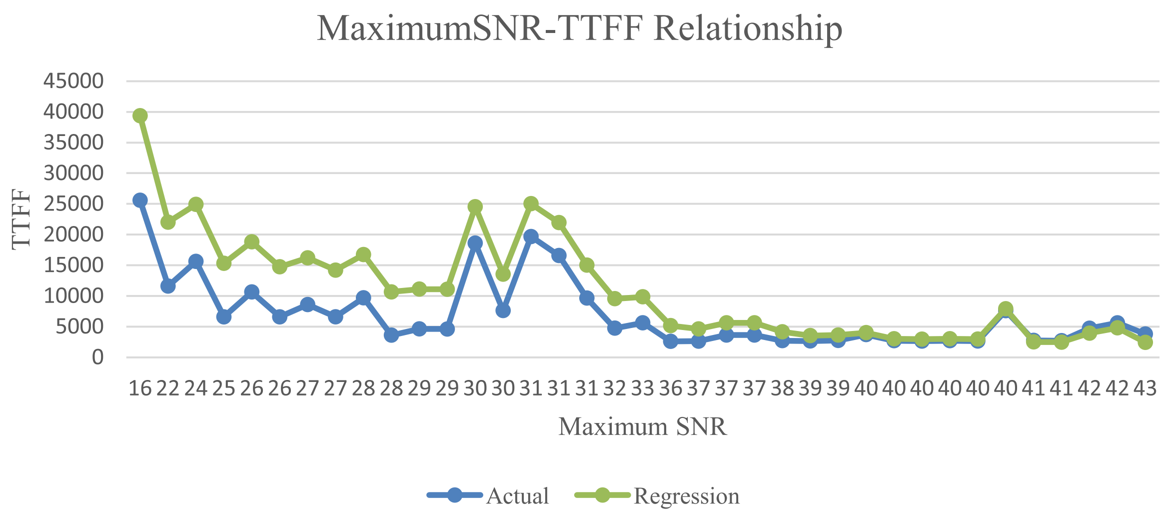

FIGURE 7. **Maximum SNR-TTFF relationship.**

following equation:

$$E = 0.0797 * TTFF$$

Where E is the consumed energy during TTFF and TTFF is Time To First Fix. It is clear from Figure 8 that there is a strong linear relationship between the fixing time - time needed to find InView satellites and decide which satellites to use (InUse satellites) and finally calculate the location coordinates- and energy consumed from battery. Long TTFF implies weak GPS satellites signal strength and according to the next figure (figure 8) energy consumptions increases as TTFF increases which means that energy consumption increases as signal strength gets weaker (long TTFF). Conversely short TTFF implies strong GPS satellites signal strength and according to the next figure (figure 8) energy consumption decreases as TTFF decreases which means that energy consumption decreases as signal strength gets stronger (short TTFF).

C. SNR AND CONSUMED ENERGY RELATIONSHIP

In the previous two subsections, we formulate the relationship between maximum and minimum SNR and TTFF and between TTFF and energy. From these relationships, we can find the relationship between maximum and/or minimum SNR and energy.

By using the relationships Energy-Minimum SNR and Energy-TTFF, we found the following formula:

$$\begin{aligned} SNR &= -679.8 + 21831 \\ E &= 0.0797 * TTFF \\ E &= 0.0797((SNR - 21831)/-679.8) \end{aligned}$$

Where E is energy, SNR is minimum GPS satellite signal strength, and $TTFF$ is Time To First Fix. Figure 9 validates our assumption of GPS satellites signal strength impact on energy consumption rates and it is clear that consumed energy decreases when SNR increases.

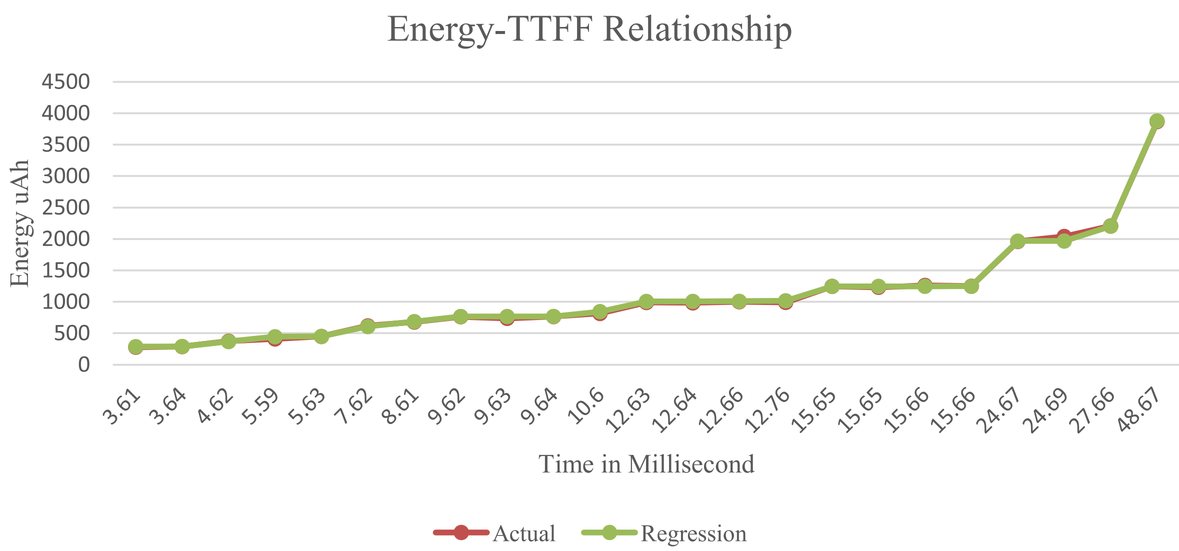

FIGURE 8. Energy-TTFF relationship.

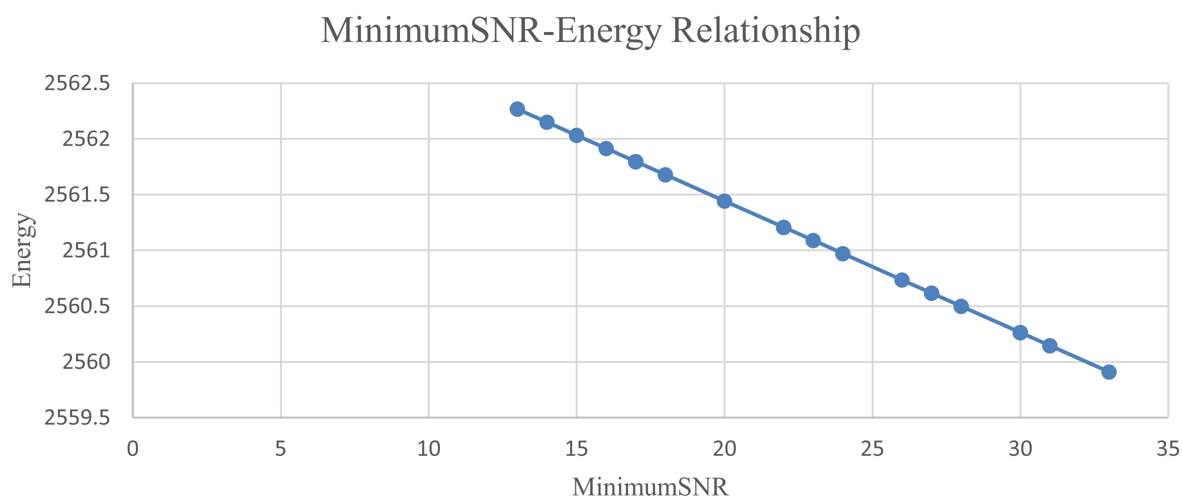

FIGURE 9. Minimum SNR-energy relationship.

VII. CONCLUSION AND FUTURE WORK

Smartphones are increasingly playing an essential role in our move towards smart cities era. The battery lifetime of handheld devices is one of the most important parameters in achieving good user experience for the handheld devices. Therefore, the management and optimization of handheld device applications in relation to their power consumption is an important area of research.

In this paper, motivated by the fact that location-based applications are among the top power-hungry applications, we have performed a measurement study of GPS satellites signal strength. Our analysis has shown that users encounter large variations in the strength of the GPS signal while using various applications requiring access to their locations. We also performed experiments to quantify the energy consumption of locating specific points using GPS under poor and good signal strengths. Our experiments on running two LBAs outdoors and indoors and observing battery consumption rates show that only 13% of the mobile battery is drained under good signal strength and about 38% of the mobile battery is drained under weak signal strength.

We designed a new android application, GPS listener that gives a detailed account of localization processes for specific locations. Using this application, and the Monsoon application, we observed power consumption rates and how it relates to TTFF lengths under various signal strengths of InUse satellites. Subsequently, we developed a mathematical model to investigate the relationship between the energy consumption of a localization application and the strength of the GPS signal. The results demonstrated that higher SNR values of GPS signals do consume less energy while low GPS signals causing faster battery drain.

To the best of our knowledge, this is the first study that provides a quantitative understanding of how the poor strength (SNR) of satellite signals will cause relatively higher power drain from a smartphone's battery. This work is an important step towards understanding the power usage of location based applications. Future work will look into further evaluation of the proposed model and explore strategies to reduce power consumption of location based applications.

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