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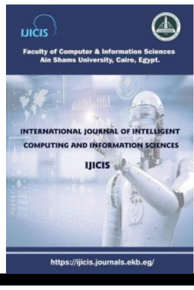

PROPOSED METHODOLOGY FOR BATTERY AGING AND DRAINAGE MITIGATION

Yusuf Awad*
Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt
yusufmamdouh.std@cis.asu.edu.eg

Islam Hegazy
Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt
lslheg@cis.asu.edu.eg

El-Sayed M. El-Horbaty
Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt
shorbaty@cis.asu.edu.eg

Abstract: *A longer battery life is a highly sought-after feature for most smartphone users when considering their next device. However, with the emergence of new hardware technology and software applications that require heavy processing, the demand for battery power has significantly increased. Unfortunately, the development of battery technology has not kept up with the rapid advancements in smartphone hardware and software, which rely heavily on battery power. To address this issue, several approaches have been proposed to regulate battery consumption and the charging process on smartphones. In this paper, we summarize the different approaches related to this problem that managed to achieve up to a 61% increase in battery daily usage in simulation testing, highlighting their strengths, limitations, and current challenges. Furthermore, we provide a comprehensive review of various open-source datasets that have the potential to be used in developing new approaches to improve battery drainage and degradation in smartphones. We also discuss the methodology for collecting each dataset. Finally, we propose a new approach to address the current limitations and challenges to solving the problem of battery drainage and degradation that could be developed using the currently available datasets. These new approaches may involve incorporating Machine Learning (ML) techniques to predict battery charging patterns and minimize battery drainage.*

Keywords: *Smartphone Battery, Battery Drainage, Battery Degradation, Charging Prediction, Intelligent Charging.*

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1. Introduction

The lithium-ion (Li-ion) battery plays a crucial role in powering the various components of today's smartphones. As new technologies and features are incorporated into smartphones, the demand for more power is increasing, according to research conducted by Allied Market Research [1]. As a result, it is predicted that the mobile battery market will grow to a staggering $38.6 billion by the year 2030. However, there is a limitation to the amount of capacity a battery can provide, which is determined by

***Corresponding Author**: Yusuf Awad

Faculty of Computer and Information Sciences, Ain Shams University, Cairo, Egypt

Email address: yusufmamdouh.std@cis.asu.edu.eg

the battery's cell design. Furthermore, this capacity deteriorates over time as the battery undergoes charging and discharging cycles.

The degradation of a battery can result in a reduction in the amount of energy it can store, which can lead to the battery failing to perform as it was designed to. There are several factors that contribute to battery degradation, including temperature, charge and discharge voltage, current, and the level at which the battery is charged or discharged. By understanding these factors, it may be possible to slow down the rate of battery failure and extend the lifespan of batteries, thus allowing them to better serve their intended purpose. Failure to address battery degradation can result in an increase in e-waste, which is a growing concern worldwide. According to a report from The Conversation [2], the global use of electric and electronic equipment is increasing rapidly, with smartphones making up 12% of the total. This percentage is expected to rise in the future, according to the Environmental Coalition on Standards [3] and Committed to Connecting the World [4], and as a result, the total amount of e-waste is projected to double by 2030. Unfortunately, only a small fraction of e-waste is formally collected and recycled, with only 17.4% of 2019's e-waste being recycled. While the amount of recycled e-waste has increased by 1.8 million tons each year between 2014 and 2019, the total amount of e-waste has grown by 9.2 million tons over the same period. Furthermore, the amount of undocumented e-waste is also increasing, which could pose additional environmental and health hazards.

In recent years, smartphones have undergone rapid development and have become an essential device for many people due to their ability to perform a variety of complex tasks. They can be used for productivity, gaming, and streaming, making them highly versatile. Furthermore, smartphones have evolved into rich-sensor devices over time, leading to the replacement of single-purpose devices like GPS and digital cameras. This has resulted in smartphones being a rich source of large-scale data that can be used to better understand ourselves, our usage patterns, and our needs. As a result, numerous datasets have been collected from smartphones for various purposes while ensuring the privacy and confidentiality of users. These datasets can be extremely valuable in addressing a wide range of problems, and we will explore some of them in later sections. Battery optimization and prolonging battery life have become major research topics as the need to minimize e-waste has become increasingly important to the industry.

The rest of this paper is organized as follows: Section 2, provides an overview of the background information. Section 3, presents the related work and summarizes novel, state-of-the-art work that decreased the rate of battery degradation and extended the battery lifecycle. Section 4, discusses the different available datasets and their collection methods. Section 5, illustrates the proposed methodology for further enhancement. Finally, Section 6, summarizes our findings and discusses future work.

2. Background

2.1. Battery Charging

The process of charging the battery has a higher impact on its aging than the process of discharging it, as it was investigated by Chen, Yukai, et al. [5]. That is why a Constant Current-Constant Voltage (CC-CV) protocol is being used in the charging process of Li-ion batteries as a standard protocol due to its advantage of affecting battery aging [6]. The CC-CV comprises two distinct stages, as illustrated in Figure 1. In the initial stage (CC), the battery undergoes charging at a consistent current until its voltage reaches a predetermined threshold. In the subsequent stage (CV), the battery experiences charging at a constant voltage until the current diminishes to a predefined level.

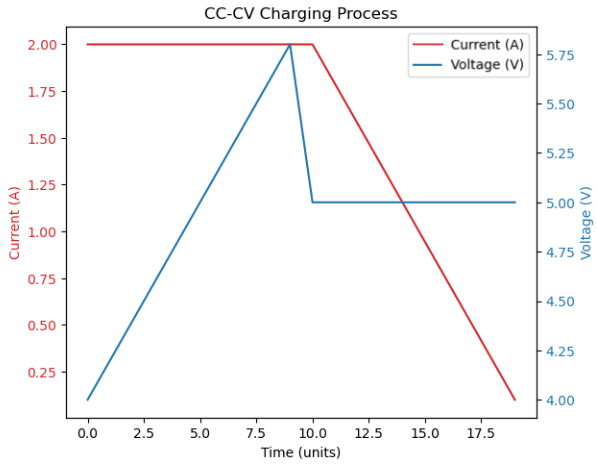

Figure. 1: Illustration of CC-CV charging process

2.2. Battery Aging

In recent years, battery aging concern has increased due to climate problems that call for using clean and renewable sources of energy, and batteries ability to store energy has caught attention. Which makes solving the battery aging problem a must. But in order to solve this problem, we need to understand the different factors that lead to battery aging.

According to Xiong, Rui, et al. [7] factors that contribute the most to battery aging are temperature, charge-discharge rate, and depth of discharge. Temperature is the most contributing factor to battery aging, based on Guan, Ting, et al. [8] work that showed that 45 °C causes 10 times more capacity degradation damage than 25 °C on a battery. The charging rate can also significantly impact the aging of a battery [7]. Rapid charging at high rates can lead to elevated temperatures within the battery. Excessive heat accelerates chemical reactions within the battery, contributing to faster degradation. Also, higher charging rates impose greater stress on the electrodes. This stress can cause physical changes, such as the expansion and contraction of electrodes, leading to mechanical wear and tear. Finally, the least contributing factor to battery aging is depth of discharge (DoD), according to Watanabe, Shoichiro, et al. [9]. Deeper discharges result in more significant chemical reactions within the battery. This can accelerate degradation processes, leading to a shorter overall lifespan. Also, high DoD values put more stress on the electrodes and other internal components of the battery, contributing to mechanical wear and degradation.

In summary, battery aging is primarily influenced by temperature, charge-discharge rate, and depth of discharge. Temperature emerges as the most impactful factor, with research showing that a temperature increase from 25 to 45 °C can cause ten times the capacity degradation damage. Charging rate significantly affects aging, as rapid charging at high rates elevates temperatures, accelerating chemical reactions and causing mechanical wear on electrodes. The depth of discharge, identified as the least contributor, leads to significant chemical reactions and stress on internal components, accelerating degradation and shortening the overall battery lifespan.

3. Related Work

Extending battery usage time and lifespan has garnered substantial attention in recent research, experiencing significant growth over the past decade. Numerous studies have concentrated on optimizing the charging process of batteries, recognizing its pivotal role in influencing both the lifespan and usage duration of batteries. In this section, we will initially provide a summary of notable work that proposes new intelligent charging methodologies aimed at minimizing battery aging. This involves the meticulous control of factors that have the greatest impact on battery aging during the charging process. Subsequently, we will summarize state-of-the-art research efforts dedicated to mitigating battery drainage.

3.1. Intelligent Charging Approaches

Recently, academics have made significant efforts to prevent overcharging during the charging process, which results in high temperatures—an influential factor in battery aging. Overcharging often occurs due to users' charging routines, particularly when they charge their smartphones overnight while sleeping, leaving the device connected to the charger for an extended period. To address this issue, researchers have introduced various methodologies for developing an intelligent charging process that effectively prevents overcharging.

Pröbstl, Alma, et al. [10] presented a novel context-aware charging approach to tackle this problem. The main objective is to lower the target state of charge that is sufficient for the user's daily usage instead of fully charging the battery to 100% and shift the start of the charging process so that phones' batteries do not overcharge, causing their lifespan to degrade. The user either enters the parameter manually, retrieves some of these parameters from the OS-provided APIs, or predicts them through the charging behavior for the last five days. Those required parameters are the target state of charge, the medium state of charge, and the target time for unplugging the charger. At first, when the user plugs in the charger, the battery starts to charge to a medium state of charge, which is a safety margin in case the phone is unplugged earlier than expected. After that, the charging process stops and resumes before the target time for unplugging the charger. This time parameter was either provided by the user, retrieved from the OS APIs, or estimated from the past pattern of the user's charging behavior to reach the target state of charge without letting the battery be overcharged. The solution could be implemented fully as software, but due to the non-standardization of the API being provided by different OS, a software-hardware solution is easier to implement by inserting a switch and microcontroller in the supply lines of the USB cable. The microcontroller receives data and instructions from a client application that is installed on the smartphone. The results showed an increase in smartphone lifespan by an average of two years in a simulation test.

Ghassani, Faza, et al. [11] proposed a similar approach, but instead of using a predictor algorithm, the system uses a trained ML algorithm deployed on a remote server, and communication happens between the server and the microcontroller. The schema consists of three layers: the first layer is a client application installed on the smartphone that sends data about the charging state of the battery to a remote server, and the second layer is a microcontroller and a switch integrated within a USB supply cable, as depicted in Figure 2. The microcontroller communicates with the client application to stop charging based on the data being received from the model passed through the client application so that an overcharging would not happen. Finally, the last layer is the server, which collects the data from the application every ten minutes and sends a response to the microcontroller through the client application with a value of 0 in case the state of charge does not reach 100% and 1 otherwise. The third layer is also responsible for using the collected data to train the KNN algorithm to classify whether a full charge was reached or not. The classification result that was made by the KNN is being sent to the microcontroller. The KNN with two classes scored 0.78 in the F1-Score in a real-world test on one user.

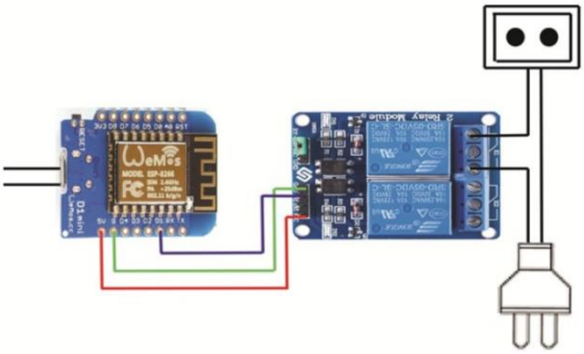

Figure. 2: Integration of the microcontroller within the USB supply cable [11]

A battery automatic system, exclusively available for Android smartphones, has been proposed by Djuanda, D. S. R., et al. [12], achieving an impressive accuracy rate of 100%. The proposed system, as illustrated in Figure 3, comprises a mobile application installed on the smartphone, enabling users to set the target state of charge (SoC). This application connects to a microcontroller via smartphone Bluetooth. The microcontroller oversees the charging process to prevent overcharging. This is accomplished by receiving the target SoC, with the default value set at 100% if no target SoC is specified, and monitoring the current SoC. Once the current SoC reaches the target value, the microcontroller communicates with a relay connected to the charger, prompting it to switch from a closed to an open state, thus concluding the charging process. Finally, the mobile application notifies the user to disconnect the device from the charger.

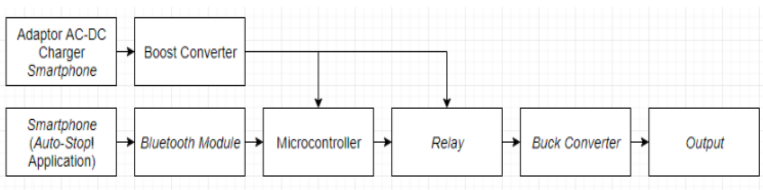

Figure. 3: System block diagram illustrating Djuanda proposed solution [12]

A more intricate approach, proposed by Raura, Geovanny, et al. [13], limited to Android devices, aims to mitigate the impact of DoD during the charging process. Instead of charging the battery from 0% to 100% in one continuous cycle, this solution divides the process into two stages. The method involves reducing the target SoC to a set threshold, maintaining this threshold for a specified time interval by decreasing the current, and then completing the charging process until the battery reaches its full capacity.

The solution comprises three main components: the FIWARE platform, an open-source framework for accelerating the development of IoT solutions installed on a server, a mobile application, and a microcontroller. The primary purpose of the FIWARE platform is to retrieve the current SoC of the battery through the mobile application, write this information into a database, and compare it with the target SoC. Once the current SoC reaches the threshold, the platform communicates with the microcontroller using a publish/subscribe pattern to lower the electric current, maintaining the current SoC until another communication occurs to complete the charging process. Users can set the threshold through the mobile application.

From the industry side, both Apple and Google introduced Optimized Charging and Adaptive Charging [14,15] in iOS 13 and Android 11. Both of these features split the charging process into two phases. In the first phase, the battery is charged normally until it reaches a specific target state-of-charge (SOC), usually around 80%. Then, the second phase begins by slowly charging the battery, lowering the input voltage until it reaches 100%. The drawback for both of these features is that they only work with users who have a specific charging routine. It takes fourteen days to learn this routine, and they are only initiated for the longest charging session within this routine, which must exceed 3 hours. Lastly the battery could reach high temperature during the first phase of charging.

Table 1 provides a comprehensive summary of the outcomes from the previously discussed research on intelligent charging approaches, highlighting the various metrics and methodologies used for measurement.

Table 1 Summary of intelligent charging approaches results and limitations

Conducted By	**Results**	**Limitations**
Pröbstl, et al. [10]	Achieved an increase in battery lifespan by a factor of 1.8 in simulation testing. Regarding predicting the charging session time, a result was not reported.	A modification to the charger is needed.
Ghassani, et al. [11]	Achieved an F1-Score metric of 0.78 for predicting the ending of a charging session.	Integrating a switch within the USB supply cable is needed.
Raura, et al. [13]	No result was reported. Further work will be conducted to measure the effects of the proposed solution on battery aging.	Limited only to the Android OS.
Djuanda, et al. [12]	Achieved an accuracy rate of 100% in terminating the charging session once it reaches the predetermined target SoC.	Limited only to the Android OS.
Apple and Google [14, 15]	No result was reported.	Only works with users that have charging routines, it takes 14 days to learn the user’s charging routine, it works only with charging sessions that exceed 3 hours within the user’s routine, and there is no guarantee that it will prevent the battery from reaching high temperatures during the charging session.

3.2. Mitigating Battery Drainage Approaches

Other researchers worked on mitigating the battery drainage challenge, which indirectly causes battery aging, such as Peltonen, Ella, et al. [16, 17]. They presented a recommendation engine for smartphones based on a trained decision tree that proposes to the user actions for changing some system settings that cause battery drainage. For example, it notifies the user to turn off the WiFi in case it is not connected, which drains energy. Those actions result in prolonging the usage time of smartphones. The trained decision tree is deployed on a server, and a client application is installed on the smartphones that communicates with the server, sending the current system settings and status for the smartphone, and the server responds with an actionable recommendation to be taken in order to increase the usage time of the smartphone's battery without affecting the user's usage experience. The model was trained by mutual information metrics for energy rate consumption for system settings and status that were driven from the Carat Dataset [18]. This approach resulted in reducing the battery train by up to 61% and improving battery usage time in real-world testing under specific circumstances.

Wei, Kun, el al. [19] developed a battery-aware protocol that alternates application behaviors to consume less energy while maintaining the user experience. The protocol monitors two things in the battery: the voltage and the current, or how much electricity is being used, and it keeps track of these things all the time. A trigger time is being preset. If the battery's parameters act in a certain way for longer than the preset time, for example, when it's using a lot of electricity for a while, the protocol starts working. When the protocol is initiated, it looks at all the apps running and sees if some can be slowed down a bit without causing any problems. If it finds one, it decides when to slow them down. This helps save the phone's resources and the network's resources. After the preset time, your phone checks if it can keep those apps off or if they need to be turned back on. If it can't find any apps to turn off, it resets the trigger time and starts tracking the battery's parameters again. This keeps happening in a loop. Because of this loop, the battery gets used up in a different way, and it lasts longer. So, this smart plan helps your phone's battery stay healthier by making it work in a way that matches how batteries naturally behave. It's like a little helper that makes sure your phone stays charged for a longer time. An experiment was conducted on a streaming music app by playing ten songs, each five minutes in length and ten megabytes in size. After applying the battery-aware protocol, compared to the regular behavior, there was an 8.5% improvement in battery life when the preset trigger time was set to be five seconds and a 10% improvement when it was set to be one second.

Govindan, Kannan, et al. [20] proposed TCP Closure Optimization (TCO) to enhance battery life, which involves altering the behavior of TCP at the application layer on the client side. It is a client-side solution only, thus making deployment easier. TCO solves the problem of FIN retransmission that happens when the application moves to the background and then moves back again to the foreground. It then sends FIN to close the TCP connection, which has already been released by the server after the timeout, causing an energy drain. TCO detects closures of TCP connections after identifying the delayed connections, as shown in Figure. 4. TCO performs TCP closures on those connections, achieving 10 to 20% energy savings.

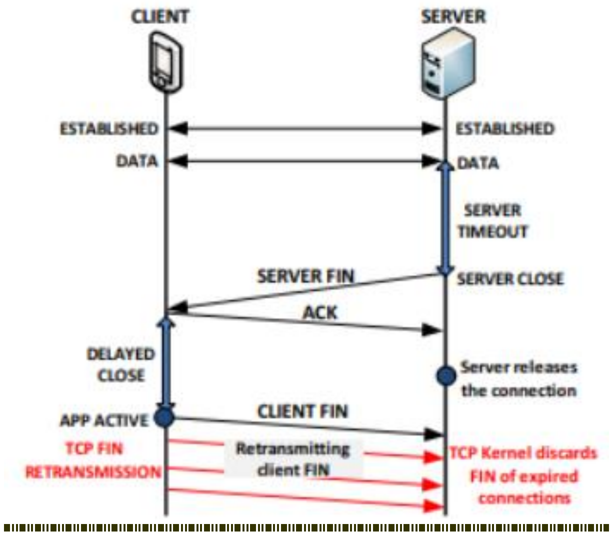

Figure. 4: Illustration of FIN Retransmissions and TCP Delayed Closures [20]

Furthermore, a battery drain testing and diagnostic tool has been developed by Jindal, Abhilash, et al. [21]. This tool facilitates developers in conducting both short and extended automated tests to identify battery leaks that may occur during user interaction with the application. Initially conceived as a prototype for academic research, further examination of the industry revealed a notable demand for such a tool. Many developers lack automated testing methodologies for battery drainage, and some do not assess their applications for potential battery leaks. The tool provides developers with actionable insights through a dashboard that displays a power consumption timeline for the application while it runs on the device. It is important to note that this tool is currently only available for Android.

Lastly, Google introduced Extreme Battery Saver [22] in 2020, which is a feature enabled by the user by setting a target percentage value for the battery; when this value is reached, the feature is activated automatically. Google claims that this feature could extend the battery usage time up to 72 hours. However, it has limitations, such as pausing most apps from working in the background, which can block any important notifications that could be received from any app, turning off some features like location, and slowing down the processor.

Overall, most of the currently proposed approaches are limited to testing only in simulation; no real-world testing has been conducted, which makes these approaches questionable for real-world applications. Regarding the industry approaches, they have a major limitation that make them not work properly, especially the deployed feature for intelligent charging as it does not work properly with users who don't have a specific charging routine. Furthermore, no end-to-end solution has been proposed to address both the problems of battery overcharging and battery drainage and is not limited to any OS, which will result in decreasing battery aging. Our proposed methodology addresses these open problems.

4. Dataset Overview

Smartphones have become an invaluable source of data due to the advanced technology incorporated into them, such as plenty of sensors and powerful processors, that generate enormous amounts of data. However, the various types of data generated by smartphones require different collection methods to extract relevant information accurately. There are three primary collection methods for smartphone data:

1. Surveys: Surveys are a simple yet effective way of gathering data. They involve answering predetermined questions, sometimes with predefined answers, that researchers design for a specific study. Despite their simplicity, surveys are not any less important than other methods.

2. Monitoring apps: App monitoring has become a crucial task in app development. It involves logging the user's interactions with an app to catch any bugs that may arise during production.

3. App stores: The app store method involves collecting metadata from various stores, such as the App Store for iOS or Google Play for Android. This metadata includes information such as the app category, number of downloads, and ratings.

Different datasets are collected based on different collection methods. For instance, the Worldwide Survey Dataset [23] was created by conducting a survey to collect specific information for particular goals. On the other hand, the iOS Apps Dataset [24] project aimed to extract metadata about apps from the App Store.

In conclusion, smartphones provide an immense source of data, and different collection methods are necessary to gather the relevant information accurately. The choice of collection method depends on the type of data required, and each method has its advantages and limitations.

In this work, we are particularly interested in datasets that were produced using the monitoring app method since this type of dataset is the most valuable when addressing the issue of battery degradation as it usually includes battery information at each point in time along with the operation, the application that was running, and system settings that cause a change in battery. In this regard, we will provide an overview of two of the most informative datasets that were collected using the monitoring app method, namely LiveLab [25, 26] and the Carat dataset [18].

LiveLab Dataset: This dataset was collected exclusively from iOS users using the monitoring app method. It comprises data from 24 volunteer students at Rice University, Houston, Texas, USA, from February 2010 to February 2011. The data includes software interactions, such as the currently running apps and foreground apps, the category of each app, the timestamp for how long an app was open, web browsing history, and the OS state. It also collected contextual information about the devices while maintaining user privacy and confidentiality, such as GPS location, battery status, WiFi signal, associated WiFi, available WiFi, cell signal, cell tower information, and display information. Although informative, the dataset suffered from skewness as it consisted of only one type of OS, one type of smartphone brand, and users from the same geographical location. However, this also makes the dataset suitable for hardware-level studies.

Carat Dataset: The Carat dataset was collected through a monitoring app called Carat that can be downloaded from the App Store or Google Play Store. This app monitors user usage and logs changes in battery percentage. The dataset was collected from 2014 to 2018, covering over 500 million users in 100 different countries, and consists of 18,146,042 timestamped records. The dataset also collects data at both the software and hardware levels. The major drawback of the Carat dataset is that it does not collect metadata about the devices and the hardware and sensors in those devices. Nonetheless, it remains an essential resource for analyzing battery degradation issues and can be used in various studies.

In conclusion, both the LiveLab and Carat datasets provide valuable insights into smartphone usage and battery degradation. While the LiveLab dataset suffers from some skewness, it remains suitable for hardware-level studies. On the other hand, the Carat dataset is more comprehensive but lacks metadata about the devices and hardware.

5. Proposed Methodology

Based on the previous work, there is no complete approach that both prolongs battery usage time and battery lifespan. An end-to-end approach would be more convenient for the user and more practical. Interval charging is more effective than shifting the start of processing charging for prolonging battery lifespan. This is because reducing the voltage rate of the charging and increasing the charging time causes less battery degradation and does not increase the battery temperature during charging, as it was proven [10]. The technique of intermittent charging will be applicable through studying the user's charging pattern using an ML algorithm for prediction. The ML algorithm will predict the time interval for each charging session using the user's historical charging data to train on. After that we will deploy the trained ML algorithm on a remote server. The remote server will communicate the predicted ending time of a charging session to an IoT device through a mobile application, as depicted in Figure. 5. The IoT device would be responsible for regulating the charging process and splitting it into charging intervals and not charging the battery to its full capacity before the predicated ending time of the charging session. This will not only prevent overcharging the battery, which results in overheating the battery, but also, as the battery will be charged in time intervals, this will give the advantage of not reaching high temperatures while the battery is being charged, and those two factors will reduce battery degradation that happens while charging. The distinguishing factor between our proposed solution and Ghassani's lies in the implementation approach. Ghassani's solution necessitates the integration of a switch and microcontroller within the USB supply cable, as illustrated in Figure. 2. Conversely, our solution employs IoT devices that are connected to the charger, with the USB supply cable being subsequently connected to these devices.

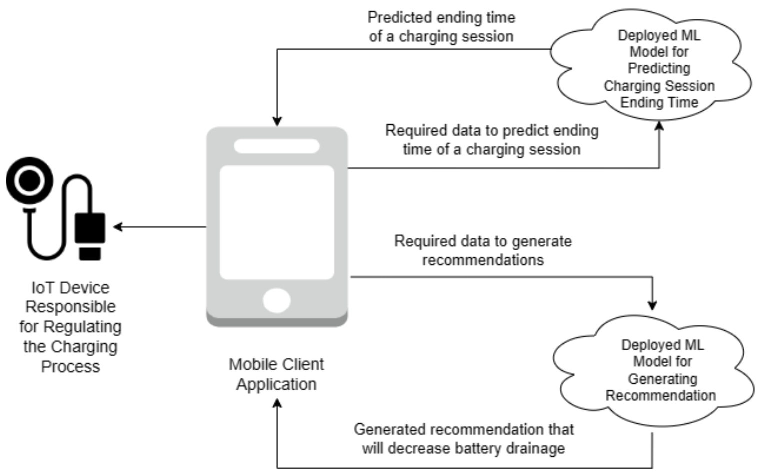

Figure. 5: Proposed architecture for our solution

To prolong battery usage time, we are proposing to build a recommendation engine using an ML algorithm. We train an ML algorithm on user usage and its affect on battery capacity data to generate recommendations. These recommendations are actions to be taken that will not affect the user experience while using the smartphone. These action are reminder to the user that a specific feature is being enabled while being not made use of it and it consumes power that leads to battery drainage. For example, notifying the user to switch off the Bluetooth in case nothing is connected to it or switching to cellular data if the WiFi signal is weak and drains more energy. The ML algorithm will be deployed on a remote server, as shown in Figure. 5, and will be communicated with through a client application that will need to be installed on the user's smartphone. The generated recommendations will be based on the user's usage, and these recommendations will regulate the user's usage of the smartphone, leading to less battery drainage without affecting the normal user experience.

In our future work this proposed methodology will be implemented, benchmarked it with previous works, and incorporated real-world testing which is crucial for validating the robustness and effectiveness of proposed methodologies. While simulation testing provides a controlled environment to evaluate theoretical concepts, the transition to real-world scenarios is indispensable for ensuring practical viability and identifying potential challenges that might not be evident in simulated conditions.

6. Conclusion and Future Work

This work has provided an overview of prior endeavors focused on extending battery lifespan and enhancing usage duration. Additionally, we went through available potential datasets suitable for future investigations in this domain, as they contain the minimum required information to tackle this problem, which is user interaction with the smartphone and its effect on power consumption. While our exploration predominantly centered on software-based power management approaches, it is vital to note that simulation-based assessments were conducted for certain methodologies. It's worth acknowledging that these simulations could engender outcomes not entirely reflective of real-world scenarios, owing to the complexity of battery dynamics during charging and discharging processes, which remain partially enigmatic.

Thus, to attain results with a higher degree of truth, it is imperative to undertake empirical testing in real-world settings. Our deliberation of datasets predominantly spotlighted those obtained via a monitoring application, a highly promising resource for addressing this uncertainty. This dataset type encapsulates a comprehensive historical record encompassing usage patterns and charging behaviors, indispensable for resolving both the challenges of extending battery life and usage duration.

Finally, we have introduced a holistic methodology designed to enhance both battery usage longevity and overall lifespan. We strongly advocate for the practical validation of our proposed methodology through rigorous real-world experimentation in the future. This will not only contribute to advancing our understanding but also furnish actionable insights into the real-world efficacy of the suggested approach.

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