Evaluating Battery Aging on Mobile Devices

Jaeseong Lee, Yohan Chon, Hojung Cha
Department of Computer Science
Yonsei University, Seoul, Korea
{jslee, yohan, hjcha}@cs.yonsei.ac.kr

ABSTRACT

Battery-related problems in mobile devices have been extensively investigated in both industry and literature. In particular, battery aging is a critical issue, since battery lifetime decreases as usage time increases. Battery aging primarily causes inconvenience to users by necessitating frequent recharging, and also affects the accuracy of power estimations for mobile devices. Evaluating battery aging and its effects has rarely been addressed in prior works. In this paper, we propose an online scheme to quantify the battery aging of mobile devices. Specifically, we estimate the degree of battery aging as a ratio metric based on patterns of charging time. For example, an estimate of 50% indicates that the battery capacity is only half of full capacity, meaning that the battery usage time is only approximately half that of the new battery's. Our scheme works autonomously on mobile devices and does not require any external equipment. The extensive experiments demonstrated that the proposed scheme quantifies battery aging accurately.

Categories and Subject Descriptors

D.2.8 [**Metrics**]: Product metrics

General Terms

Management, Measurement, Experimentation

Keywords

Mobile System, Battery Aging, Smartphone, BMU

1. INTRODUCTION

Energy consumption in mobile device is a critical issue. Extensive research has been conducted in recent years for power modeling of mobile devices [1, 2], and also for various energy management schemes [3, 4]. However, previous work has rarely addressed the issues associated with battery hardware itself, such as the aging phenomenon, which significantly affects the usage time of mobile devices. Battery aging is defined as the performance or health of a battery tends to deteriorate or diminish gradually due to irreversible physical and chemical changes that take place with usage [5]. For example, different batteries of the same type may derive different usage times for the same workload. Previous work [1] used external equipment to deliver power into mobile device to eliminate the effect of battery aging. In practice, however, the characteristics of the battery, especially with regard to battery aging, should be carefully considered as they pertain to energy management on mobile devices.

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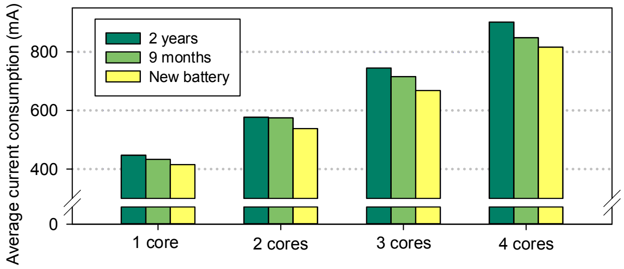
Battery aging leads to reduced usage times for mobile devices [6]. In the worst cases, batteries would not practically be usable at all due to the significance of usage time degradation. In addition, battery aging results in inaccuracy of power estimations of mobile devices, and consequent inconvenience to users due to the need for frequent recharging. Frequent recharging may even cause device failure because of the selling effect (i.e., the battery is inflated) [7]. Commercial mobile platforms such as Android provide battery health information via a battery charge chip, but the notifications are limited to case of exceptional status (i.e., the available voltage is less than 2.7 V or the battery is unable to be used because of high temperature). For the pragmatic use of a battery, accurate and meaningful information about battery status should be provided to both mobile users and researchers in the field.

The battery aging issue is closely related to the chemical characteristics of the lithium ion (Li-ion) batteries commonly employed in modern devices. First, batteries are known to consume more power (e.g., 4.3 V) than what is required in mobile devices (e.g., 4.0 V), due to both the heating effect and the fundamental limitation of battery schematics [8]. Second, the relationship between battery capacity and charging/discharging time is not linear [9, 10]. The particles of Li-ion move slowly at high battery levels due to a high density of particles, and vice versa. For example, 15 minutes is necessary for charging a battery by 10% from 5% to 15% of its capacity, but the same 10% increase requires 46 minutes to increase the charge from 90% to 100% level. This phenomenon indicates that the charging/discharging time of a battery varies despite constant current consumption by the device. Estimation of battery aging is thus challenging due to the complicated characteristics of battery hardware.

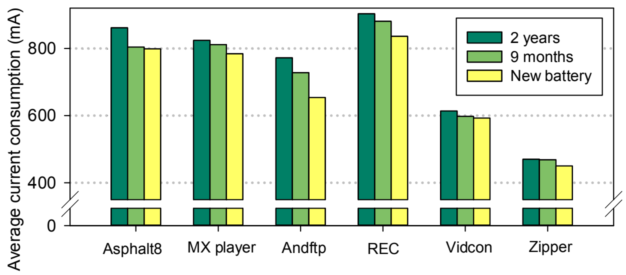
In this paper, we propose an online scheme that quantifies battery aging in mobile devices without external equipment. We calculate the degree of battery aging as a ratio metric. For example, an estimate of 50% indicates that the battery capacity is only half of full capacity. We quantify the battery aging based on the charging duration. Specifically, our system uses the linearity of charging duration per 1% battery level, and compares it with the charging duration on a brand new battery. The information obtained from charging time can be directly used at discharging, since the charging and discharging patterns are known to be symmetric in Li-ion batteries [11, 12]. The extensive experiments conducted with 9 batteries validate that the proposed scheme provides accurate information about battery aging in mobile devices.

2. RELATED WORK

Research has been conducted to understand the chemical characteristics of Li-ion batteries [9, 10]. The relevant studies have proposed a method of combining chemical elements to



(a) Number of enabled cores



(b) Real application

Figure 1. Average current consumption using three batteries with different ages (2 years, 9 months, the brand new one).

overcome the limitation of Li-ion. Petricca et al. [13] designed a battery schematic to obtain battery health information. The work was, however, based on simulations, not on real mobile devices. Additionally, the battery aging issue has been specifically discussed in the chemical engineering community [14]. Previous work, however, has rarely considered the battery aging issue in mobile devices. Kim et al. [8] noticed that batteries consume more power (e.g., 4.3 V) than required in mobile devices (e.g., 4.0 V), and the difference in power consumption is large in aged batteries. This observation indicates that battery aging should seriously be considered in power management for mobile device.

Battery aging affects the accuracy of power modeling for mobile devices [1]. Most researches [1] have designed power models based on power measurement by external equipment. The models would not, however, be practical since the characteristics of battery aging were ignored. Dong et al. [2] proposed an online model using a battery management unit (BMU) rather than external equipment. The practical limitation of this approach is that many commercial smartphones do not provide the current information in BMUs.

3. MOTIVATION

We motivate our work by investigations of the battery aging issue through preliminary experiments. Specifically, we present our findings regarding the degradation of battery usage time caused by battery aging. We first present the battery aging effect on three batteries with different ages (2 years, 9 months, and a brand new one). We used a Samsung Galaxy S3 (GT-i9300) smartphone and measured its power consumption using the PXI-1033 and the PXI-4070 [15]. In the experiment, we used the BMU equipped in the phone to obtain the remaining capacity of battery in terms of a ratio to full capacity.

To investigate the difference in power consumption resulting from battery aging, we compared the average current used to perform the same task from 80% battery level down to 10% level. Figure 1(a) shows the results of performing a task with 100% CPU utilization with a different number of cores. The results indicate that the average current alters according to the batteries.

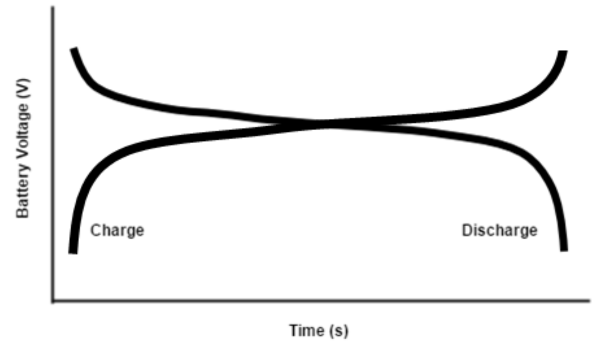


Figure 2. Battery voltage for charging and discharging on Lithium-Ion Battery [11, 12]

Interestingly, the average current consumption using the 2-year-old battery is larger than that using the relatively new ones. Similar results were obtained when we ran six real applications, as shown in Figure 1(b). The net result of the experiment is that the difference in aging level led to different usage times of the device, from 1 hour to 5 hours.

Our preliminary findings are as follows. The efficiency of battery indeed varies depending on the degree of battery aging. The usage time for old batteries is shorter than for the new one for the same workload. The findings indicate that battery aging should be carefully reflected in power-related research, such as power modeling and energy estimation. In addition, the experiment well explains user dissatisfaction with aged mobile devices. In summary, accurate information about battery aging would be useful for both mobile users and researchers in the field.

4. Estimating Battery Aging

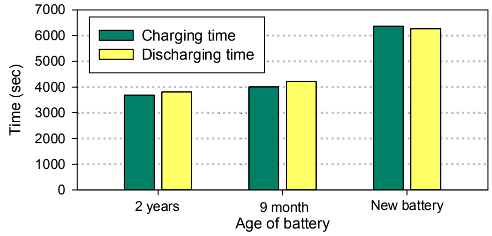
We now present a scheme that quantifies battery aging as a ratio metric. We design the empirical solution since the reliable model for extrapolating battery charging and discharging is not available yet.

4.1 Charging Characteristics

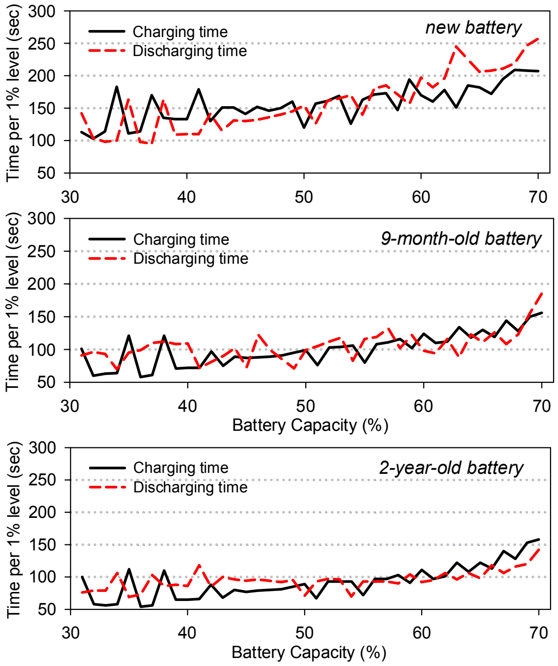
An intuitive way to estimate battery aging is to measure the current consumption of the battery. The BMU in a mobile device provides the current consumption of the battery, but its update rate (i.e., 0.25Hz to 4Hz) is typically too low to trace the current with the required granularity (i.e., more than 10kHz). In addition, commonly-used BMUs such as TI's BQ27x00 [16] do not provide current information at all. Thus, we need an alternative method to estimate battery aging, rather than the use of current consumption.

To address this issue, we consider that the charging and discharging curves are symmetric on Li-ion batteries [11, 12], as illustrated in Figure 2. The idea is that if we could estimate the battery capacity upon charging, it would be directly used to estimate the battery capacity upon discharging. In other words, we can estimate battery aging without information about the current consumption of the actual hardware device.

We empirically validated the symmetric relationship between the charging and discharging times of a battery. We applied a constant current to the battery using external equipment, and measured the current upon both charging and discharging. Figure 3(a) shows the charging/discharging time from 30% battery level up to 70% battery level. The result indicates that the duration varies depending on battery aging, yet the charging time and discharging time are similar with only a 3.2% difference. Figure 3(b) shows the trace of charging/discharging time from 30%



(a) Charging and discharging time between 30% and 70% battery level



(b) Trace of charging and discharging time

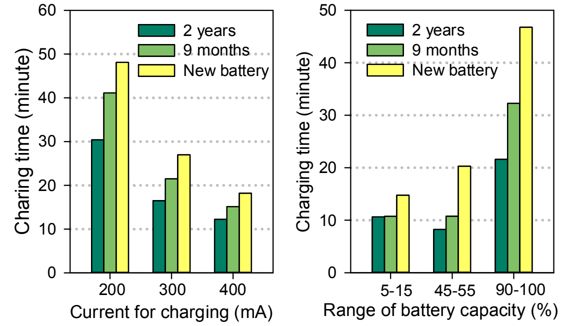
Figure 3. Pattern of charging time and discharging time on three batteries with different ages (2 years, 9 months, and brand new one).

battery level up to 70% level. The charging time showed only a 3.3% difference in discharging time. The experiment shows that the relationship is indeed symmetric.

We further investigated the relationship between battery aging and charging time. For example, an old battery requires a relatively short charging time, since its performance is worse than that of new one. For the experiment, we charged the batteries via USB and set the current to 200 mA, 300 mA, and 400 mA. Figure 4(a) shows the charging time from 70% battery level up to 80% on three different batteries (2 years, 9 months, and a brand new one). The charging time on the 2-year-old battery is 11.3±5.9 minutes (average±deviation) less than that on the new one. The trend is the same with different battery levels, although the duration varies from 8.2 minutes to 46.8 minutes according to battery level, as shown in Figure 4(b). At low battery level (i.e., 5% to 15%), the difference in charging time between batteries is less (12 minutes) than the difference (33 minutes) at high battery level (i.e., 90% to 100%). The result indicates that battery aging derives a short charging time as well as a short discharging time across all battery levels.

4.2 Linearity in Charging Time

Knowing that charging time varies with both battery aging and battery level, this section examines the inherent pattern in the relationship between battery aging and charging time. In our scheme, we only considered charging by USB cable and AC

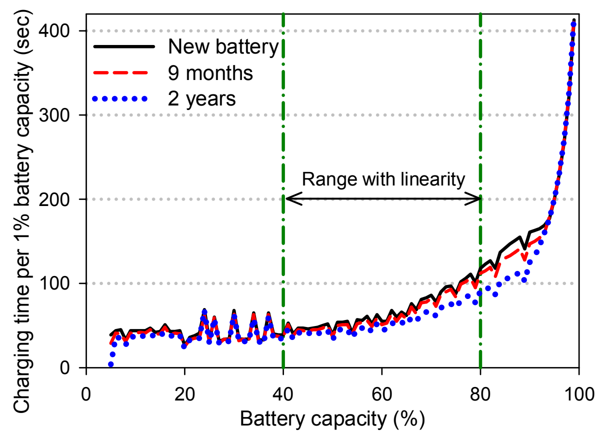


(a) 70% to 80% charging interval (b) Use of 466 mA current

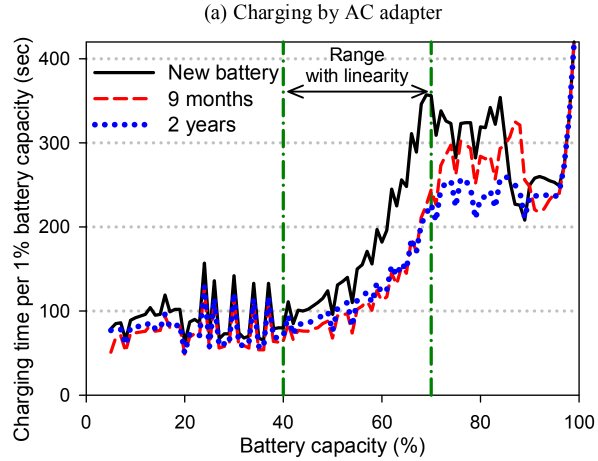
Figure 4. Comparison of battery charging time on three batteries according to (a) charging current and (b) battery capacity.

adapter which are common in practice. The charging current is accessible in online.

Figure 5(a) and (b) show the charging time of a Li-ion battery from 0% battery level up to 100% by AC adapter and USB cable, respectively. From the results, we can categorize the charging interval into three sections: the low region, middle region, and high region. In the low region (i.e., less than approximately 40% battery level), the charging time per 1% battery level mostly fluctuates since the particles of Li-ion are moving fast due to the low density of particles. In the high region (i.e., greater than approximately 80% battery level), the charging time rapidly increases. The most interesting, however, is the middle region, in

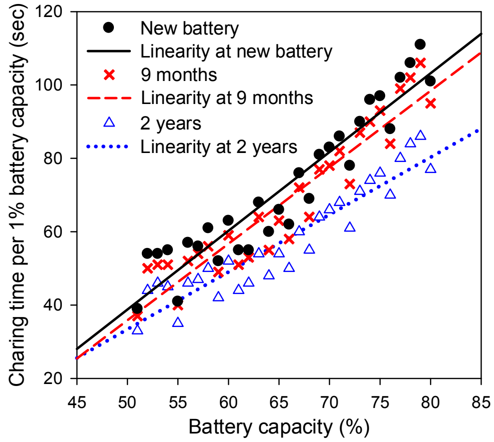


(a) Charging by AC adapter

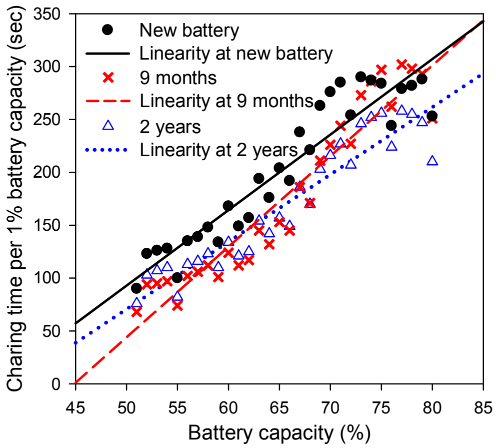


(b) Charging by USB

Figure 5. Trace of charging time of Li-ion Battery.



(a) Charging by AC adapter



(b) Charging by USB

Figure 6. Linear regression analysis in the middle region of the charging time. Linearity is measured by the linear regression.

which the charging time increases at nearly a linear rate. In other words, charging time and battery level exhibit a nearly linear relationship. Thus, we focus on the middle region of battery level in order to make use of the linearity between charging time and battery level.

Figure 6(a) and (b) show the charging time in the middle region (i.e., from 45% battery level up to 85% level). We conducted the experiment three times for each case and applied the linear regression. The charging time is linear at this interval with a 0.89 and 0.90 adjusted R^2 value for charging by AC and USB, respectively. Note that large R^2 value indicates high linearity. The results indicate that use of charging time within the middle region is appropriate to quantify battery aging since it displays a clear linearity with minimum noise.

4.3 Estimation Algorithm

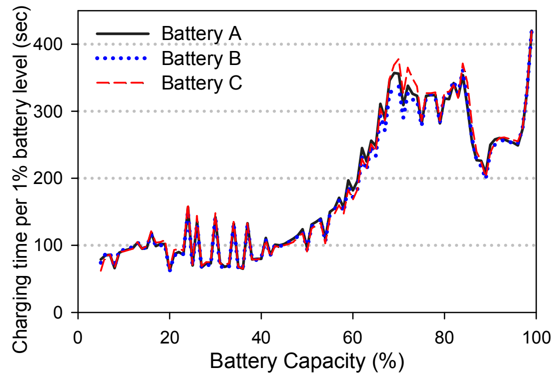
We developed an algorithm to quantify battery aging as a ratio metric. In our work, we define battery aging as the ratio of actual usage time to theoretical usage time at full capacity. Battery aging is then expressed as *battery efficiency* since the usage time of an old battery lessens with aging. In other words, battery aging results in decreasing battery efficiency.

To quantify the battery efficiency, our scheme estimates (1) the range of the middle region $[\alpha, \beta]$ that exhibits the linearity of charging time, (2) the theoretical charging time of given range $T^{theory}_{[a,b]}$, and (3) the actual charging time of given range $T^{actual}_{[a,b]}$. The battery efficiency E is then calculated as follows:

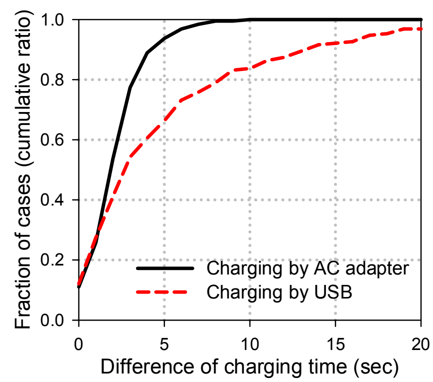
$$E = \frac{T^{actual}_{[a,b]}}{T^{theory}_{[a,b]}} \text{ where } \alpha < a < b < \beta.$$

We first determine the middle region in order to minimize noise associated with charging time, as described in Section 4.2. We use the least squares method, which is widely used in linear regression. Briefly, the method estimates the linear function $y = ax + b$ given n samples with minimum error e. In our case, x is the given battery level (e.g., 15%) and y is the charging time at a given battery level (e.g., 50 seconds). Our scheme determines $[\alpha, \beta]$ based on the pattern of charge time in the new battery, to divide the trace of charging time into three parts $[0, \alpha], [\alpha, \beta], [\beta, 100]$. Note that $[\alpha, \beta]$ indicates the range from an α% battery level up to a β% level. The error in each part is denoted in least squares regression as $e^{low}, e^{middle}, e^{high}$, and we iteratively identify an $[\alpha, \beta]$ that minimizes the summation of errors $e^{low} + e^{middle} + e^{high}$. Here, we restrict the value as $\alpha < 50\%$ *and* $\beta > 50\%$ based on the characteristics of the Li-ion battery (see Figure 2) as well as on our own observation (see Figure 5). Given n samples, the complexity of the algorithm is $O(n^3)$, but the computation time is trivial since n is, at most 50, as in our case.

The theoretical charging time T^{theory} is calculated using the charging pattern on a new battery. Figure 7(a) shows the trace of charging time on three brand new batteries[1]. The trends are nearly



(a) Trace of charging time



(b) Difference of charging time per 1% battery level between three new batteries

Figure 7. Charging time of three new batteries and its difference.

[1] The battery model is EB-H1G6LLU.

Table 1. Discharge time and measured efficiency

Battery	Discharge time (min)	Measured efficiency		Range
		AC	USB	
A	93.17	-	-	Reference
B	92.15	0.971	0.982	[44,57]
		0.927	0.974	[50,60]
C	91.92	0.905	0.957	[45,55]
		0.923	0.953	[50,60]
D	81.77	0.880	0.886	[45,57]
		0.879	0.878	[50,60]
E	77.62	0.840	0.825	[48,68]
		0.833	0.806	[50,60]
F	67.62	0.698	0.664	[46,54]
		0.692	0.628	[50,60]
G	67.28	0.730	0.707	[44,59]
		0.730	0.676	[50,60]
H	66.68	0.678	0.751	[52,65]
		0.687	0.744	[50,60]
I	55.93	0.694	0.654	[45,65]
		0.708	0.627	[50,60]

the same for new batteries. Actually, 90% of differences of charging time are less than 4.1 seconds and 13.2 seconds for AC and USB charging, respectively, as shown in Figure 7(b). In other words, one-time learning on a new battery could be used as the reference data. Thus, in the proposed scheme, we calculate T^{theory} for a new battery powered by AC and USB cases *a priori*. The limitation of this scheme is that the estimation of charging time should be performed at least once for each battery model. We discuss this limitation in Section 6.

The next concern is the acquisition of the actual charging time T^{actual}. Commercial mobile platforms such as Android provide the charging status and the charging types (i.e., AC adapter or USB cable). Since battery capacity can be measured from BMU, we can measure T^{actual} in online when a user charges his/her phone. The given range $[a, b]$ is determined during charging where $\alpha < a < b < \beta$.

For example, in a certain battery, the theoretical charging time from a 50% battery level up to a 60% level $T^{theory}_{[50,60]}$ is 750 seconds with the AC adapter. The actual charging time $T^{actual}_{[50,60]}$ is shorter (e.g., 375 seconds) than $T^{theory}_{[50,60]}$ due to battery aging. The battery efficiency E amounts to $0.5 = 375/750$.

5. EVALUATION

We evaluated the accuracy of the proposed scheme on the Samsung Galaxy S3 (GT-i9300). The standard capacity of the battery employed in the device is 2100 mAh with 3.8 V. The battery efficiency E is evaluated for charging by both the AC adapter and a USB cable.

5.1 Detecting Linearity in Charging Time

For the experiment, we used 9 batteries with a spectrum of battery ages. Of 9 batteries, three are brand new and denoted as Battery A, B, and C. The remaining 6 batteries are denoted as Batteries D to I.

The scheme first determines the middle region that shows the linearity between charging time and battery level. Figure 8 shows the trace of charging time on batteries and the selected region as a blue dot line in the figure. $[\alpha, \beta]$ is empirically determined in Battery A as [44%, 69%]. The computation time of detection is 1.84ms in the Ubuntu machine. Within a given range, the linearity of charging time and battery capacity is observed across all batteries, as shown in Figure 8(a-e). The adjusted R^2 value in linear regression is 0.68±0.07 (average and deviation) and 0.80±0.06 at case of AC charging and USB charging, respectively, as shown in Figure 8(f). The old batteries tend to show larger errors than the new ones, but it still shows linearity (e.g., R^2 value is 0.73 for Battery H and 0.62 for Battery I). The results show that the detected middle region $[\alpha, \beta]$ in a brand new battery could be applied to other batteries.

5.2 Accuracy of Battery Aging Metric

We now evaluate the accuracy of the proposed scheme. The ground truth of battery aging is, in fact, not known. Thus, we empirically estimated the ground truth of battery aging. We measured the discharge time of each battery three times from 100% battery level down to 0% for the same workload. The discharge time of new batteries is 92.2±0.6 minutes, and that of the rest of the batteries varies from 56 minutes to 92 minutes, as shown in

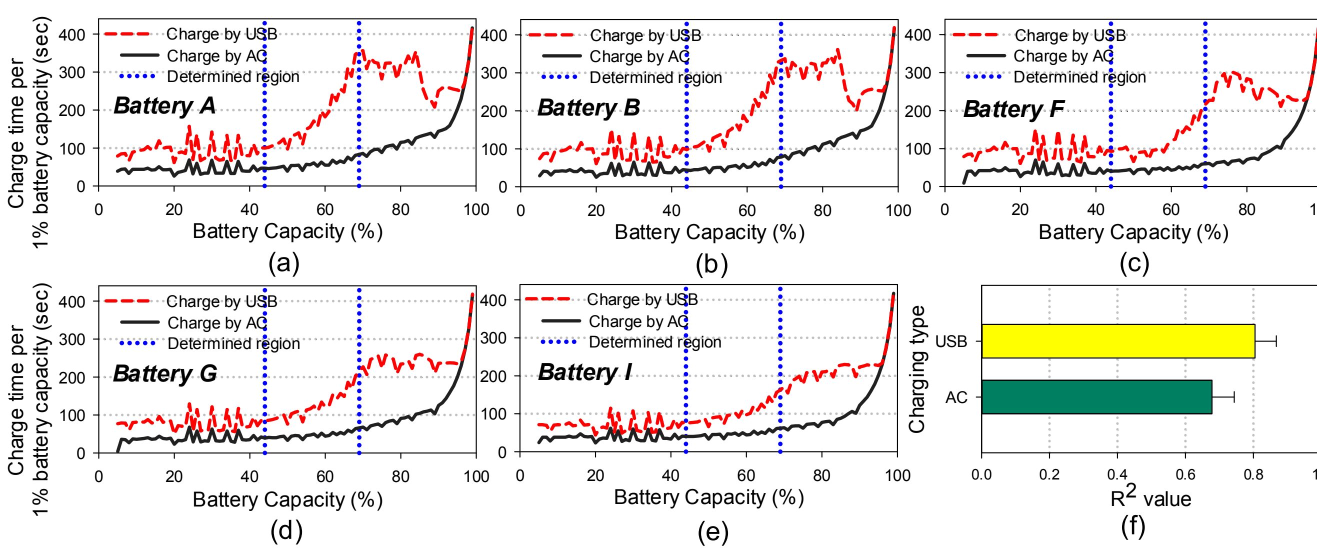


Figure 8. Trace of charge time for (a) battery A, (b) battery B, (c) battery F, (d) battery G, (e) battery I; (f) R^2 value in linear regression for all batteries. Large R^2 value indicates high linearity.

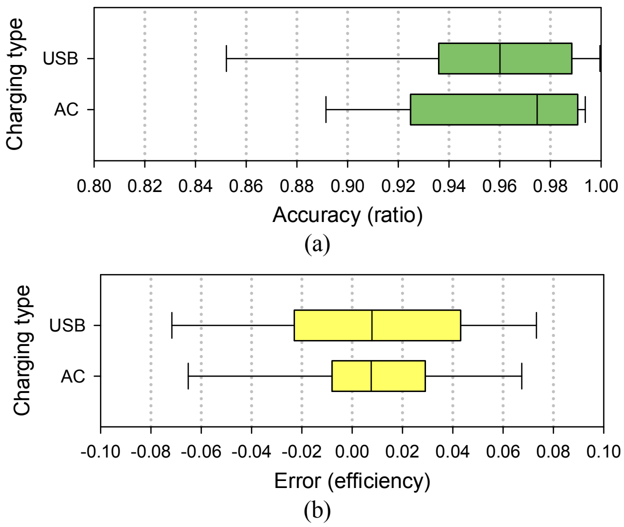


Figure 9. Box-and-whisker plot of (a) accuracy and (b) error of the proposed scheme on 8 batteries. Box indicates first percentile, median, and third percentile, and whisker indicates 10th and 90th percentile.

Table 1. Here, we used the pattern of Battery A as the reference data.

We then applied the proposed scheme to 8 batteries in order to quantify the battery efficiency E during charging via AC and USB. We chose a diverse range $[\mathrm{a}, \mathrm{b}]$ within $\alpha < a < b < \beta$. Table 1 shows the measured battery efficiency with several ranges $[\mathrm{a}, \mathrm{b}]$. The brand new batteries showed almost 100% efficiency: that is, 0.95±0.03 efficiency. The efficiency of the rest of the batteries varied from 0.63 to 0.89, and the different ranges for each battery derived similar efficiency with only 3.7% difference.

We then calculated the accuracy of the proposed scheme by comparing the measured efficiency with the manually calculated one. The error is the difference between the efficiency and the manual calculation, such as $\mathrm{error}^x = (D^x/D^{new}) - E^x$. The accuracy of efficiency for battery x is then defined as:

$$\mathrm{accuracy}^x = 1 - \frac{|error^x|}{(D^x/D^{new})},$$

where E^x is the measured efficiency for battery x, D^x and D^{new} are the discharge times of battery x and the new battery running the same tasks, respectively. Figure 9 shows the accuracy and the error of the proposed scheme. Our scheme derives 0.94±0.05 accuracy with a range from 0.82 to 0.99. The largest error (i.e., approximately -0.11) is observed with old batteries (i.e., battery H and I) with AC charging. The reason for this is that the fluctuation of charging time is relatively large with old batteries. The error varies from -0.11 to 0.09, as shown in Figure 9(b). The result indicates that the proposed scheme provides accurate and robust information with various batteries.

6. CONCLUSION

We proposed a scheme that quantifies battery aging as a ratio metric. Our scheme automatically estimates battery aging without external equipment. To the best of our knowledge, we are the first to propose a metric that quantifies the degree of battery aging in mobile devices. We believe that the proposed scheme can serve as a building block for diverse power management schemes for mobile devices, as well as an intuitive indication of battery age for mobile users. The power management scheme may exploit our metric for estimating experimental errors caused by the aging factor. Users are also able to replace their batteries in a timely manner through the use of our scheme.

The present scheme requires preliminary training in charging pattern at least once for each battery model. Although the overhead is trivial, the training may be opted out of by using a crowdsourcing-based scheme. For example, the charging time for a specific battery could be compared with the charging time of a huge number of batteries used by a crowd. Such a crowdsourcing-based statistical method has been recently studied in energy-related research for mobile devices [17].

7. ACKNOWLEDGMENTS

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