Fingerprinting Battery Health Using Relaxing Voltages

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ABSTRACT

Mobile devices are only as useful as their battery lasts. Unfortunately, the operation and life of a mobile device's battery degrade over time and usage. The state-of-health (SoH) of batteries quantifies their degradation, but mobile devices are unable to support its accurate estimation — despite its importance — due mainly to their limited hardware and dynamic usage patterns, causing various problems such as unexpected device shutoffs or even fire/explosion. To remedy this lack of support, we design, implement and evaluate `V-Health`, a low-cost user-level SoH estimation service for mobile devices based only on their battery voltage, which is universally available on all commodity mobile devices. The design of `V-Health` is inspired by our empirical finding that the relaxing voltages of a device battery *fingerprint* its SoH, and is steered by extensive measurements with 15 batteries used for various commodity mobile devices, such as iPhone 6 Plus, Nexus 6P, Galaxy S3, etc. These measurements consist of 13,377 battery discharging/charging/resting cycles and have been conducted over 72 months cumulatively. `V-Health` has been evaluated via both laboratory experiments and field-tests with multiple Android devices over 4–6 months, showing <5% error in SoH estimation.

CCS CONCEPTS

• **Hardware → Batteries**; **Power and energy**; • **Computer systems organization → Embedded software**.

KEYWORDS

mobile devices, battery aging, relaxing voltage

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1 INTRODUCTION

Background. Apple announced a free-replacement program of iPhone 6S batteries in Nov. 2016, due to frequent users' complaints on the phone shutoffs even when showing 10–30% remaining power, and concluded faster-than-normal battery degradation to have caused the problem [4]. Similar unexpected phone shutoffs also occurred on devices such as Nexus 6P, Galaxy S4, iPhone 5, to name a few [26]. These incidents imply the inability to accurately answer a simple question "*how long will my phone battery last?*", which means (i) the remaining battery life (e.g., relative to battery degradation and thus its warranty period) or (ii) remaining device operation time until the battery runs out (i.e., the operation time with a single charge). The answer relies on the quantification of battery's capacity degradation, which is traditionally captured by its *state-of-health* (SoH), defined as the ratio of the battery's full charge capacity to the designed capacity.

Unfortunately, not all mobile devices are equipped with the capability necessary for accurately quantifying its battery's SoH, introducing errors in estimating the devices' remaining power (i.e., state-of-charge (SoC)) and thus shutting them off prematurely or unexpectedly [1, 23, 34]. The deficiency of health information on mobile devices' batteries stems from the non-existence of compatible methods to estimate their SoH. Most existing SoH estimation methods require either battery parameters, determination of which is beyond mobile devices' capability due to hardware limitation (e.g., impedance [14, 15, 49] and ultrasonic echo [40]), or specific applicable conditions that do not always hold due to devices' dynamic usage patterns (e.g., small and stable current to fully charge and discharge [48, 53]). Moreover, even Coulomb counting — the most widely-deployed SoH estimation method via current integration [31, 53] — is not supported well on mobile devices [18, 20, 52], as reported by Ampere [2], a current sensing app with millions of downloads.

Estimating Battery SoH Using Relaxing Voltages. To remedy the above problems, we propose `V-Health`, a *user-level* SoH estimation service for mobile devices based solely on their battery *voltage*, and is thus compatible to all commodity mobile devices with voltage sensing and processing capabilities, such as smartphones, tablets, smartwatches, and even electric vehicles. The design of `V-Health` is inspired by our empirical finding: the relaxing battery voltages — a time series of battery voltages when resting it after its charge/discharge — *fingerprinting* its SoH, and this voltage–SoH relationship holds reliably for all same-model batteries. We uncover and validate this property via extensive measurements with 15 batteries used for various mobile devices, such as Nexus 6P, Nexus 5X, Xperia Z5, Galaxy S3, iPhone 6 Plus, etc., consisting of a total of 13,377 discharging/charging/resting cycles and have been collected over 72 months cumulatively.

However, resting the battery to collect its relaxing voltages is not always feasible for mobile devices because they draw dynamically changing amounts of current from batteries *continuously*, even when idle [21]. `V-Health` exploits over-night device charging to collect the relaxing voltages, which (i) rests device battery after fully charging it [8, 22], (ii) offers stable battery conditions in both device operation and thermal environment, (iii) masks the disturbances caused by device usage behaviors, and (iv) is frequently done by

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users [7, 17]. Such exploitation of over-night charging in V-Health also ensures the user-perceived experience does not degrade, as the external charger supplies the power needed for information reading/logging

This paper makes the following main contributions:

- Discovery of the correlation between relaxing battery voltages and their SoH, uncovering the feasibility of voltage-based SoH estimation;
- Design and implementation of V-Health, an SoH estimation service for mobile devices via voltage fingerprinting, neither requiring additional hardware support nor incurring energy overhead that degrades user experience;
- Evaluation of V-Health using both laboratory experiments and field tests on multiple devices over 4–6 months, showing <5% SoH estimation error;

2 RELATED WORK

Accurate SoH estimation is crucial for battery management [45, 57], which has been studied extensively based on various battery parameters such as voltage [3, 24, 59], current [13, 23, 33, 39, 55], open-circuit-voltage (OCV) [25, 27, 48], SoC [10, 11], resistance [43], impedance [14, 15, 49], and even ultrasonic echo [40]. These SoH estimation methods, albeit reported to be accurate, cannot be deployed on mobile devices due to their limited hardware support and dynamic operating conditions.

Mobile devices offer limited hardware support for sensing, rendering some of the needed battery information (e.g., impedance and echo response) unavailable. Actually, even the relatively easy-to-measure electric current — the foundation of the most widely-deployed SoH estimation method, *Coulomb counting* — is not always available/reliable on mobile devices [20, 52]. Also, battery information such as OCV and SoC requires specific conditions to be met for their accurate estimation [38, 48, 53], which does not always hold due to devices' dynamic usage patterns, thus leading to up to ±25% estimation error [36]. We will make two existing solutions requiring SoC and OCV in [10, 11] adopt the over-night charge to improve reliability, and use them as the baselines for comparison in Sec. 7.

In contrast, voltage is the most pervasively/easily available battery information on mobile devices, and hence we choose its use for SoH estimation, i.e., V-Health. To the best of our knowledge, the closest to V-Health are [19] and [20].

- Guo *et al.* [19] estimates battery SoH based on its voltage–time relationship during charging. Such a voltage–time relationship, however, depends strongly on device usage behavior, making it unreliable on mobile devices. First, usage behavior during charging affects the voltage–time relationship [20]. Second, the usage behavior before device charge affects the voltage–time relationship, making [19] unreliable even when only applying it during over-night charge, as V-Health does. Fig. 1(a) plots two consecutive charges of an idle Nexus 6P phone after discharging it to 69% (1.A) and 31% SoC (2.A), respectively. Their charging phases during the [70%, 80%] SoC range (part of 1.B and 2.B in Fig. 1(a)) are compared in Fig. 1(b), showing significant differences in both durations and voltage levels and thus dependency on before-charging device usage.
- He *et al.* [20] explored the voltage-based SoH estimation based on two empirically-observed models on battery degradation. Clearly, its accuracy depends on the model accuracy and the empirically-identified model parameters, which are found to vary with battery aging. V-Health reduces such model dependencies using machine learning, which is enhanced further with a set of data pre-processing techniques including filtering, smoothing, and dimension reduction. We will use [20] as another baseline method for comparison in Sec. 7.

In summary, existing SoH estimation methods are not applicable to, or inaccurate for, mobile devices because of the non-existence of required battery information or the inability of meeting the required conditions. To remedy this problem, we propose V-Health which estimates SoH based only on voltage information and is enabled on mobile devices with the common usage pattern of over-night charge.

3 PRELIMINARIES

This section provides the preliminaries of V-Health.

3.1 Battery SoH

SoH is one of the most critical battery parameters (see Fig. 2), quantifies battery's capacity degradation, and is defined as the ratio of battery's full charge capacity $C_{\text{fullcharge}}$ to its designed level C_{design} [35, 51, 59], i.e.,

$$SoH = \frac{C_{\text{fullcharge}}}{C_{\text{design}}} \times 100\%. \tag{1}$$

SoH is also the key in estimating a battery's real-time SoC:

$$SoC = \frac{C_{\text{remaining}}}{SoH \times C_{\text{design}}} \times 100\%. \tag{2}$$

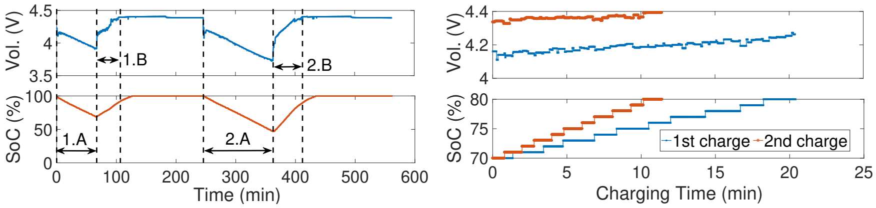
where $C_{\text{remaining}}$ is the real-time remaining capacity.

Clearly, $C_{\text{fullcharge}}$ is the foundation of SoH estimation, which is usually estimated via Coulomb counting [53, 54], i.e., integrating the current when discharging/charging the battery between two SoC levels to calculate the discharged/charged capacity as $\Delta C = \int_{t(SoC_1)}^{t(SoC_2)} i(t)dt$, where $i(t)$ is the current at time t. This way we know

$$C_{\text{fullcharge}} = \frac{\Delta C}{|SoC_1 - SoC_2|}.$$

3.2 Absence of SoH from Mobile Devices

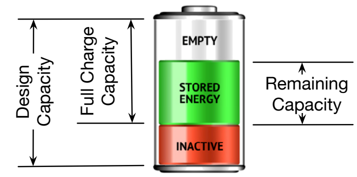
Commodity mobile devices do not support Coulomb counting well in terms of availability, accuracy, and timeliness, thus making it difficult to estimate their battery SoH. First, not all the PMICs (i.e., Power management integrated circuits), or more specifically their fuel gauge components [5], of mobile devices support current sensing [20, 52]. Moreover, the PMIC-provided current information, even when available, is very coarse [18]. Our measurement with a Nexus 5X phone shows that its PMIC's current reading deviates from the true value — collected with the Monsoon power meter at 5,000Hz — by an average of 4% even at room temperature. Lastly, the current information may lack timeliness, which is crucial for Coulomb counting because of devices' dynamic currents, i.e., varying from tens to thousands of milliamps in a few milliseconds [21].



(a) Two consecutive charges of an idle phone

(b) Both voltages & charging durations vary

Fig. 1. Device usage behavior before charging matters to [19]: (a) two consecutive charges of an idle Nexus 6P phone after discharged to different SoCs (1.A and 2.A); (b) the voltage–time relationship varies (part of 1.B and 2.B), degrading the SoH estimation accuracy of [19].



$$SoH = C_{fullcharge} / C_{design} \times 100\%$$
$$SoC = C_{remaining} / C_{fullcharge} \times 100\%$$
$$SoC = C_{remaining} / (SoH \times C_{design}) \times 100\%$$

Fig. 2. Battery SoH: quantifies its capacity degradation and is required for SoC estimation.

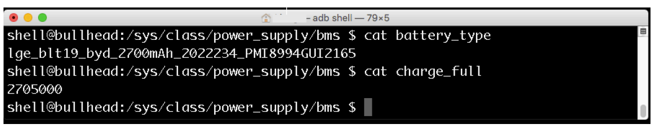


Fig. 3. Inaccurate SoH information on Nexus 5X: showing 2,705mAh full-charge capacity and thus about 100% SoH even though the phone has been used extensively for 14 months and observed to have a clearly shortened operation time.

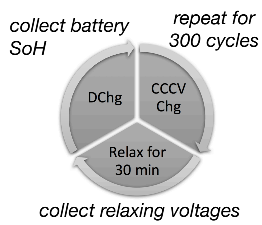


Fig. 4. Cycling measurement: charge/rest/discharge for 300 cycles.

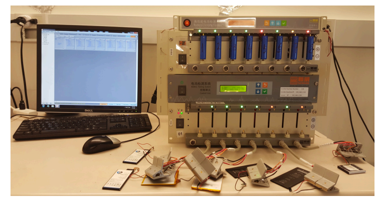
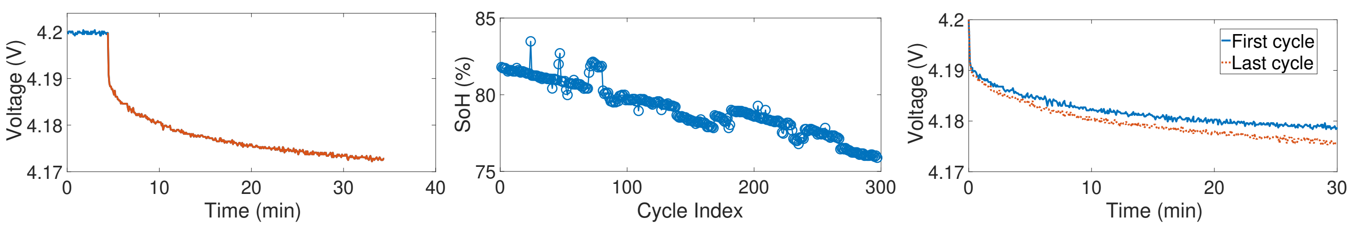


Fig. 5. BTS4000 battery tester: controls battery charge/discharge with less than 0.5% error and logs at up to 10Hz [30].



(a) Relaxing voltage

(b) SoH degrades

(c) Relaxing voltage lowers

Fig. 6. Relaxing voltage fingerprints battery SoH: (a) voltage curve during one charging/resting/discharging cycle and the relaxing voltage during resting; (b) battery SoH degrades during the measurements; (c) the relaxing voltage decreases during the measurements.

A 47% counting error due to insufficient sampling rates is reported in [20]. As a real-life evidence of mobile devices' deficiency in supporting Coulomb counting and their limited SoH information, Fig. 3 shows the full-charge capacity of a Nexus 5X phone provided by its fuel-gauge chip, saying its battery, with a design capacity of 2,700mAh, can still deliver 2,705mAh capacity upon being fully charged and thus an SoH of about 100%, even though the phone has been used extensively for 14 months and observed to have a shorter operation time. This motivates us to explore *current-free* SoH estimation, i.e., `V-Health`.

4 OVERVIEW OF V-HEALTH

`V-Health` is built on our key finding that batteries' relaxing voltages *fingerprint* their SoH. We demonstrate this finding with a 2,200mAh Galaxy S3 battery. Specifically, we test the battery by (i) fully charging it with a constant-current constant-voltage (CCCV) profile of $<0.5C, 4.2V, 0.05C>_{cccv}$ as commonly specified in Li-ion battery datasheet [32, 42], (ii) resting it for 30 minutes, (iii) fully discharging it at 0.5C-rate until reaching a cutoff voltage of 3.3V, at which mobile devices normally shut off, and (iv) repeating the process for 300 cycles, as summarized in Fig. 4. This measurement is made with the NEWARE BTS4000 battery tester [30] as shown in Fig. 5, and the cycling process (i.e., current, voltage, timestamp) is logged at 1Hz. Fig. 6(a) plots the battery voltage during one such charging/resting/discharging cycle, and highlights the relaxing voltages during resting. The relaxing voltage drops instantly upon resting and then decreases gradually further until it converges.

We collect the battery's full charge capacity (and hence its SoH according to Eq. (1)) via Coulomb counting during each discharge, thus recording its degradation process during the cycling measurement, as shown in Fig. 6(b). Also, 300 time series of relaxing voltages are collected, each during one of the 30-minute resting period (Fig. 6(c)). Comparison of Figs.6(b) and 6(c) shows that the battery SoH degrades over the cycling measurement due to its capacity degradation, while during the same measurement, its relaxing voltage decreases, exhibiting the possibility to fingerprint battery SoH with the relaxing voltages.

V-Health exploits this voltage–SoH relationship to estimate the SoH of device batteries by checking their relaxing voltages with an offline-constructed fingerprint map. Fig. 7 presents an overview of V-Health, which we will elaborate in the next two sections.

5 VOLTAGE FINGERPRINTING OF SOH

We now empirically characterize the voltage fingerprint map of battery SoH.

5.1 Data Collection

Knowledge of batteries' SoH degradation and relaxing voltages is necessary to characterize their relationship, obtaining of which requires extensive battery cycling tests. Such tests are readily available for smartphone OEMs, such as Samsung and Apple when testing their products,[1] but are not available for non-OEM researchers. Therefore, we have conducted extensive battery cycling measurements with 15 batteries used for various mobile devices as summarized in Table 1 (including the one shown in Fig. 6): collecting the relaxing voltages during each resting period and logging batteries' SoH degradation based on their capacity delivery during each discharge. These measurements consist of 13,377 cycles in total and last over 72 months cumulatively. In these measurements, the settings of $<0.5C, 4.2V, 0.05C>_{cccv}$ and $V_{cutoff} = 3.0V$ are commonly used to specify battery properties in industry during battery testing [19, 32, 42], and $V_{max} = 4.35V$ and V_{cutoff} of 3.2–3.3V specify more device characteristics: mobile devices are normally charged to a maximum voltage of 4.3–4.4V and shut off when their battery voltage reduces to 3.2–3.3V [21]. These 72-month measurements are able to identify the voltage–SoH relationship within the SoH range users experience most (e.g., users rarely switch to new batteries/devices until the old ones degrade to 0% SoH). Moreover, the thus-identified voltage–SoH relationship can be extended to the SoH ranges not covered by these measurements, as we explain later.

5.2 Construction of Fingerprint

Next we use 12 of such measurements with 4 Galaxy S3 batteries to elaborate on the construction of a voltage-based SoH fingerprint map. Each of these 12 measurements consists of ≈300 charging/resting/discharging cycles, logged at 1Hz. This way, we collected 12 SoH-degradation traces, and recorded 3, 612 time series of relaxing voltages, each from the resting period within a cycle. The same approach of fingerprint map construction is applied to all the batteries in Table 1 and evaluated, as we will explain in Sec. 7.

Data Filtering and Smoothing. Variance/noise exists in the measurements of SoH degradation and relaxing voltages (as observed in Fig. 6), which are likely due to battery dynamics, especially when considering the stable laboratory environment (i.e., with an UPS connected and room temperature control) and the battery tester's high accuracy (i.e., less than 0.5% error in controlling the cycling processes). Such a variance in battery measurements has also been reported in [19], necessitating pre-processing (i.e., filtering and smoothing) of data before constructing the fingerprint map. The collected data were filtered and smoothed using two empirically established models for the SoH degradation and relaxing voltages.

The battery health is shown to degrade approximately linearly (as observed in Fig. 6(b)) until it really becomes bad [43, 58]. To further validate this linear degradation, we tried a linear fit of the 12 collected SoH degradation processes, and all of them have an excellent goodness-of-fit in terms of root-mean-square error (RMSE) and R-Squared, as shown in Fig. 8 where each point represents the goodness-of-fit for a particular SoH degradation process. V-Health removes outlier SoH samples based on this linear model — those SoH samples deviating too much from the linear fitting (e.g., >0.5% SoH) are tagged as outliers and removed, and then the remaining samples are smoothed with a moving average.

Similarly, V-Health filters and smooths the relaxing voltages based on another empirical observation that the relaxing voltages conform to a power function $v(t) = a \cdot t^b + c$ $(t \geq 0)$, where t is the time since resting, as illustrated in Fig. 9. We apply the power fitting to the 3, 612 collected relaxing voltage traces to statistically verify this observation. Fig. 10 summarizes the goodness-of-fit — the fitting RMSE is bounded below 0.0009 and the R-Squared above 0.965, showing excellent fitting accuracy. Note that this power model differs from existing models with exponential-shape relaxing voltages [47]. Fig. 10 also plots the goodness-of-fit when fitting the same set of relaxing voltages as 1-term and 2-term exponential functions, i.e., $v(t) = a \cdot e^{t \cdot b}$ $(t \geq 0)$ and $v(t) = a \cdot e^{t \cdot b} + c \cdot e^{t \cdot d}$ $(t \geq 0)$, showing reasonably good accuracy, but not as good as the power fitting. V-Health filters the relaxing voltages with this power model, e.g., tagging the relaxing voltage traces with the bottom 5% goodness-of-fit as outliers. The moving average smoother is then used again to smooth the remaining valid relaxing voltage traces.

Note that if an SoH sample is tagged as an outlier, so is the relaxing voltage in the same cycle, and vice versa. Also, V-Health only filters out the outliers based on these empirical models, instead of using the model fitting results to construct the fingerprint map, thus alleviating its dependency on model accuracy — a clear advantage over [20]. As an example, 268 SoH samples and relaxing voltage traces are selected after the data pre-processing from the 300-cycle measurement shown in Fig. 6.

Dimension Reduction. Each of the collected relaxing voltages covers a 30-minute resting period logged at 1Hz, yielding $30 \times 60 = 1,800$ dimensions of data. Also, the voltage values in each of these dimensions are correlated. Fig. 11 plots the correlations between each pair of the 1, 800 dimensions of the 268 relaxing voltages selected from Fig. 6, where strong correlations (with correlation coefficients ≈0.8 or higher) are observed in most cases. Such highly-correlated, high-dimension relaxing voltages justify V-Health's use of the principal component analysis (PCA) for reduction of dimensions, lowering the computational effort in constructing the fingerprint map. Again, taking the measurements in Fig. 6 as an example, applying PCA reduces the relaxing voltage dimensions from 1, 800 to 35 with a variance of 99%.

[1]This also makes V-Health ideally suitable as an OEM service.

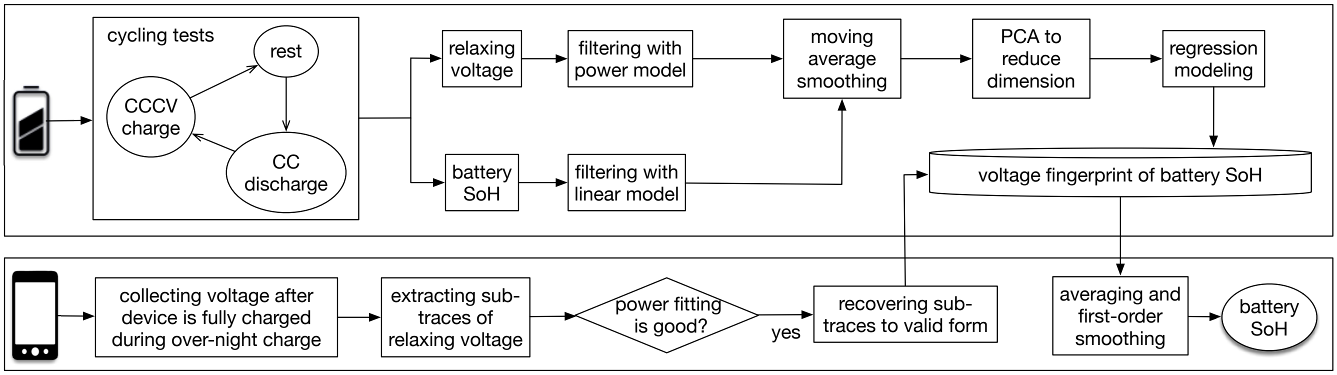


Fig. 7. `V-Health` **summary: collecting relaxing battery voltages on mobile devices and checking with the fingerprint map for SoH estimation.**

Table 1: `V-Health` **is steered and validated by 13,377 empirically collected relaxing voltage traces via 50 cycling tests with 15 phone batteries.**

Battery	Rated Capacity	# of Tests	# of Cycles	Per-Cycle Profile	Covered SoH (%)
Nexus 6P x 1	3,450mAh	5	1,300	$<$0.50C, 4.35V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[0, 93.6]
Nexus 5X x 2	2,700mAh	3	1,104	$<$0.50C, 4.35V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[59.2, 94.0]
Nexus S x 1	1,500mAh	3	150	$<$0.50C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.2V	[49.9, 54.3]
Xperia Z5 x 1	2,900mAh	5	655	$<$0.50C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.2V	[12.4, 87.1]
iPhone 6 Plus x 1	2,900mAh	2	100	$<$0.50C, 4.35V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[67.6, 79.1]
Galaxy Note 2 x 1	3,100mAh	5	1,350	$<$0.50C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.2V	[21, 96.6]
Galaxy S5 x 1	2,800mAh	3	964	$<$0.50C, 4.35V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[73.1, 91.8]
Galaxy S4 x 3	2,600mAh	8	2,374	$<$0.50C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.0V	[2.8, 93.2]
Galaxy S3 x 4	2,200mAh	12	4,800	$<$0.50C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[69.5, 97.0]
	—	4	580	$<$0.25C, 4.20V, 0.05C$>_{cccv}$; 30min rest; 0.5C DChg to 3.3V	[87.8, 92.3]

Table 2: Classification accuracy with other regression methods (%).

Battery	Linear SVM	Qua. SVM	Cub. SVM	Fine KNN	Med. KNN	Coarse KNN	Tree
#1	94	94	90	67	73	71	95.4
#2	98	94	97	92	95	95	95.1
#3	93	92	76	91	94	90	96.4
#4	91	84	70	83	92	89	97.2

Table 3: Correlated degradation.

Battery	#1	#2	#3	#4
#1	1	0.99	0.98	0.98
#2	0.99	1	0.99	0.98
#3	0.98	0.99	1	0.98
#4	0.98	0.98	0.98	1

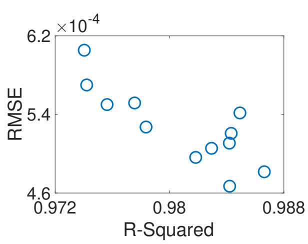


Fig. 8. Linear fitting of SoH degradation: all the 12 **degradation processes fit linearly with RMSE** <0.00062 **and R-Squared** >0.972.

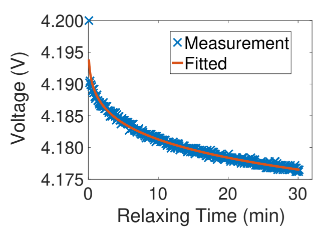


Fig. 9. Relaxing voltages are of power-shape: fitting the collected relaxing voltages to a power function $v(t) = a \cdot t^b + c$ $(t \geq 0)$.

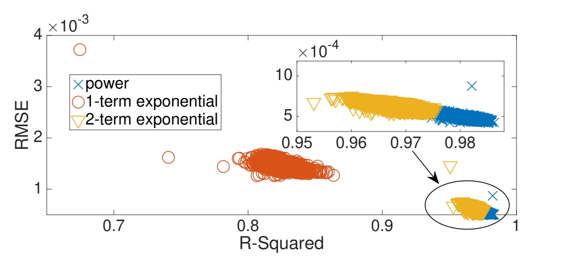


Fig. 10. Goodness of power fitting: all the 3,612 **relaxing voltage traces have RMSE** <0.0009 **and R-Squared** >0.965**; the power model describes relaxing voltages more accurately than the traditional exponential models.**

Regression Modeling. Finally, `V-Health` uses a regression tree to construct the fingerprint map, with the above-obtained principal components as predictors and the corresponding SoH as response. Fig. 12 plots the confusion matrices when validating the constructed regression model for each battery, showing over 95% classification accuracy when forming 5 SoH categories with 4% step-size. Note that this 4% step-size is only for visual clarity, and a more fine-grained step-size of 0.1% SoH is used for the evaluation of `V-Health` in Sec. 7. We have also tried other regression methods such as SVM, KNN, and their variations, but have not observed any clear advantages over the regression tree in accuracy, as summarized in

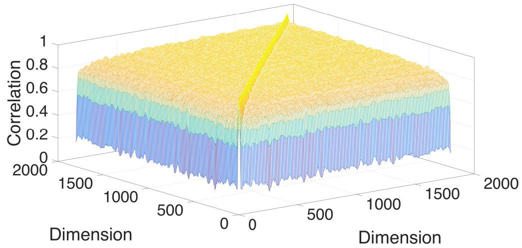


Fig. 11. Different dimensions in relaxing voltage are highly correlated: >0.8 correlation coefficients are observed for most dimension pairs.

Table 2. Thus, the regression tree is used for its simplicity and high interpretability.

5.3 Generality Analysis

The constructed fingerprint map has to be applicable for all same-model batteries, which can be verified with the following two statistical observations. First, we evaluated the similarity between the SoH degradation processes of the four batteries using dynamic time warping [29], and the resultant warping paths are close to the diagonal of the degradation matrix for each battery pair (as shown in Fig. 13), exhibiting strong similarity. Second, the SoH degradation of the four batteries used in the measurements are highly correlated, as shown in Table 3. These insights support `V-Health`'s generality of training the fingerprint map with one (or more) battery and its application to other same-model batteries, which is reasonable as same-model batteries are expected to perform similarly — a goal all battery manufactures aim to achieve [56]. We will further evaluate the cross-battery estimation accuracy in Sec. 7.

5.4 Extending Dataset

Ideally, `V-Health` is to be provided by OEMs because of their accessibility to battery cycling datasets, e.g., covering a complete battery SoH range. In case only a limited dataset is available, it can be extrapolated based on the linearity between voltage drop during resting and battery SoH. Again, we used the cycling measurements in Fig. 6 to show this observation. Fig. 14 plots the voltage drop after the battery is rested for 10, 20 and 30 minutes during the resting period of each cycle, together with the corresponding battery SoH during that cycle. A clear linearity is observed in all three traces of dropped voltages, with RMSE in the order of 10^{-4} after linear fitting. This observation enables to identify the linear coefficients based on the available cycling dataset, generate relaxing voltages that correspond to uncovered SoH, and then construct the complete voltage fingerprint map.

6 COLLECTION OF RELAXING VOLTAGES

We now describe how to collect local relaxing voltages on mobile devices.

6.1 Collection During Over-Night Charge

The relaxing voltages can not always be measured on mobile devices for the following challenges.

C1. The relaxing voltage requires batteries to be idle. We idle batteries for the 30-minute resting period in our measurements. however, mobile devices discharge their batteries with continuous and dynamic currents even in idle mode, due to device monitoring and background activities [6, 12, 21].

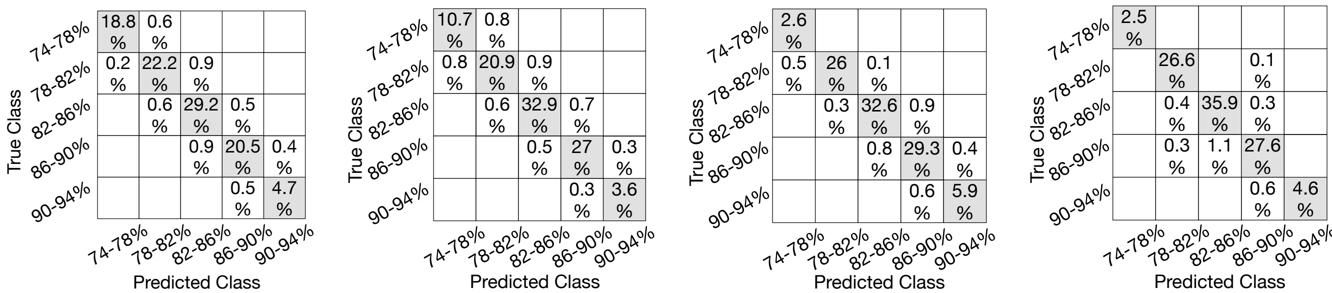
C2. Battery voltage is temperature-dependent [16, 28, 41, 50]. A stable thermal environment is thus required to collect the relaxing voltages, which is challenging due to the well-publicized device overheating problem [44].

C3. The relaxing voltage depends on its starting voltage. Fig. 15 compares the relaxing voltage when resting the battery at different voltages within [3.6, 4.2]V, showing a clear dependency between the relaxing voltage and its starting voltage level. Such dependency requires a unified starting voltage for the collection of relaxing voltages.

`V-Health` mitigates these challenges based on the fact that users often charge their devices over-night — the charging duration is so long that the charger is kept connected even after the device is fully charged. We collected 976 charge cases from 7 users over 1–3 months,[2] and found that 34% of them lasted over 6 hours and are long enough to keep the charger connected after the device was fully charged, because of the common over-night charge [7, 17, 46]. `V-Health` starts to collect the relaxing voltage once the battery reaches 100% SoC during over-night charge, and stops it when the charger is disconnected. This collection of relaxing voltages mitigates all the above-mentioned challenges.

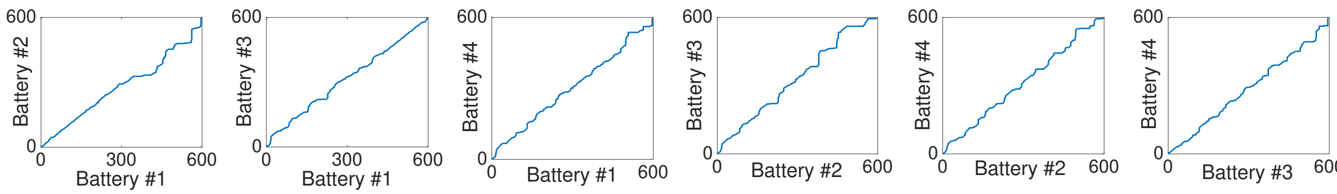
- First, over-night device charge rests its battery by powering the device operation with the charger. Commodity chargers use separate power paths to charge the battery and power the device [8], resting the battery if the charger is kept connected even after the battery reaches 100% SoC, as in over-night charge. Fig. 16 shows such rested batteries by keeping the chargers connected after fully charging a Nexus 6P and a Nexus 5X phone — the current reduces to, and stays at 0mA after fully charging the battery and thus resting the battery; the battery voltage first instantly and then gradually drops, agreeing with Fig. 6.
- Second, over-night charge provides battery a relatively stable thermal environment. Most mobile devices charge their batteries with CCCV [1], during which the CV-Chg phase takes long at a low charging rate, thus not heating the battery much and allowing for its equilibration. This way, the battery operates in a stable thermal environment during the resting period after the CV-Chg phase completes (and thus, the battery is fully charged). To verify this, we monitor the battery temperature of a Galaxy S6 Edge, a Nexus 5X, and a Nexus 6P during an 8-day real-life usage. Fig. 17 compares the temperature distribution during the resting periods after fully charging them with that under normal usage, showing reduced thermal variations, e.g., the temperature range of the Nexus 5X battery is narrowed from 25–50°C in normal case to 29–39°C when resting.
- Lastly, collecting relaxing voltages after the battery is fully charged unifies the starting voltage at the fully charged level, e.g., 4.37V for Galaxy S6 Edge.

[2] One of the user-traces was collected from our data-collection campaign and the other six traces were obtained from the sample dataset of Device Analyzer from Cambridge University [46].



(a) Battery #1 (b) Battery #2 (c) Battery #3 (d) Battery #4

Fig. 12. Confusion matrices: over 95% accuracy when forming SoH categories with 4% step-size.



(a) Betw. #1 and #2 (b) Betw. #1 and #3 (c) Betw. #1 and #4 (d) Betw. #2 and #3 (e) Betw. #2 and #4 (f) Betw. #3 and #4

Fig. 13. Similarity between degradation processes via dynamic time warping: the close-to-diagonal warping paths show similarities between individual batteries' degradation processes.

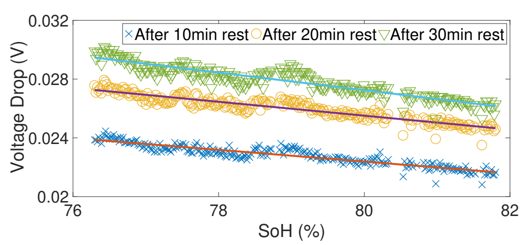


Fig. 14. Linearity between voltage drop and SoH: allows to extend the limited cycling dataset to uncovered SoH ranges, if needed.

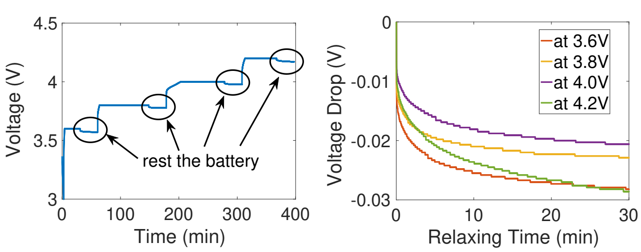


Fig. 15. Starting voltage matters: the relaxing voltage is affected by its starting voltage level, necessitating a unified starting voltage.

We must also consider if a device's usage pattern (i.e., how its battery is discharged) affects its after-charging relaxing voltages. To this end, we discharge, charge, and then rest a Galaxy S4 battery for (i) 6 cycles with different discharge currents within [300, 1300]mA (Fig. 18(a)), and (ii) another 5 cycles with a different cutoff voltage within [3.3, 4.1]V (Fig. 18(b)). The thus-collected $6 + 5 = 11$ relaxing voltage traces during each resting period are plotted in Fig. 18(c). These relaxing voltages are very close to each other (e.g., in comparison with Fig. 15), exhibiting their insensitivity to previous discharge and thus reliability — a key advantage over [19] as shown in Fig. 1. Again, this is because the charge, especially CV-Chg, of the battery masks the disturbance caused by their previous discharge from the resting period after being fully charged.

6.2 Mitigating Trickle Charge

Certain mobile devices (e.g., Galaxy S6 Edge, Galaxy S4, etc.) use trickle charge — charging a fully charged battery under no-load at a rate equal to its self-discharge rate — to keep their battery at 100% SoC, which invalidates the battery resting and thus pollutes the collected relaxing voltages. Specifically, these devices trigger trickle charge once the voltage of a fully-charged battery has dropped for a pre-defined value, e.g., 20mV for Galaxy S6 Edge and 40mV for Galaxy S4, and stop the trickle charge until the battery is fully charged again. Fig. 19(a) plots the voltage of a Galaxy S4 phone during an over-night charge, during which trickle charge is triggered 6 times after the phone is fully charged, as shown in Fig. 19(b). The duration between two consecutive trickle charges increases because the battery OCV approaches the fully-charged level.

Trickle charge prevents battery from resting and thus pollutes the relaxing voltages. `V-Health` extracts relaxing sub-traces from the polluted trace with a simple observation that a sudden increase/-drop of battery voltage indicates the triggering/stopping of trickle charge. Specifically, `V-Health` calculates the 1-lag delta voltage after the device is fully charged (Fig. 19(c)), and passes it through a low-pass filter (Fig. 19(d)). This way, `V-Health` extracts the relaxing sub-traces by locating the peaks and valleys in the trace.

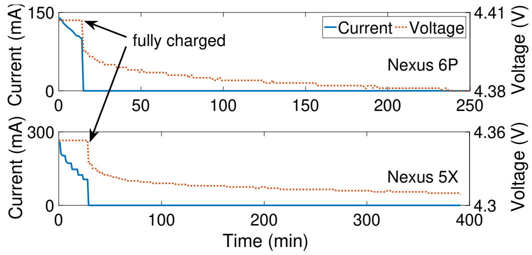
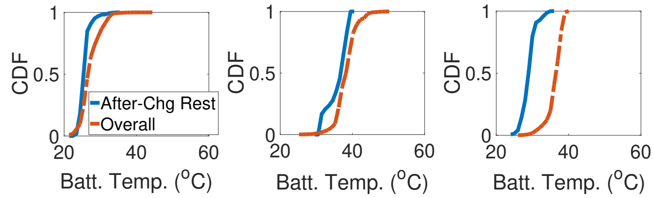
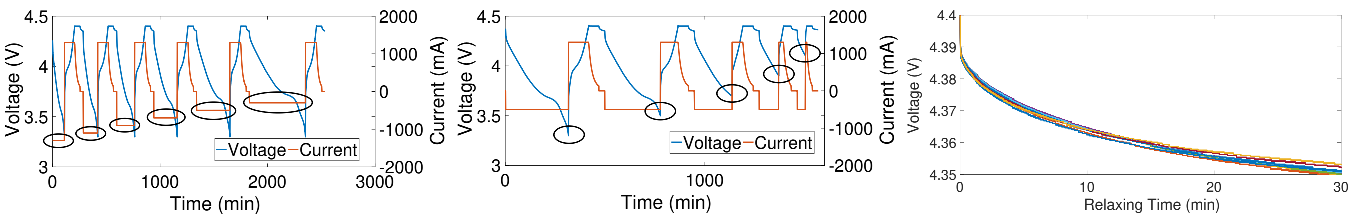


Fig. 16. Over-night charge rests battery: phone batteries are rested after reaching 100% SoC.



(a) Galaxy S6 Edge (b) Nexus 5X (c) Nexus 6P

Fig. 17. Stable temperature during resting: battery temperature during the after-charging resting period is relatively stable.



(a) DChg with different currents (b) DChg to different voltages (c) Collected relaxing voltages

Fig. 18. Relaxing voltages after charging are insensitive to discharge: relaxing voltages collected after discharging with different currents and to different cutoff voltages are close, exhibiting their insensitivity to previous discharge and thus reliability.

Fig. 20(a) plots 95 of thus-extracted sub-traces with a Galaxy S5 phone, showing the power shape but with significant variance. To further improve trace quality, V-Health applies power fitting to each of these traces, concluding them to be valid if the goodness-of-fit is acceptable. Moreover, the sub-traces may not be long enough to form a fingerprint. To remedy this problem, V-Health recovers the sub-traces to, e.g., 30-minute traces, based on the power fitting, which is then used for fingerprint checking. Last but not the least, V-Health uses the dropped voltages upon resting as the fingerprint to remove its dependency on the specific values of fully-charged voltage. Fig. 20(b) plots the processed traces based on the raw data in Fig. 20(a).

6.3 Post-Processing of SoH Estimations

Multiple relaxing traces are likely to be collected and recovered during a single over-night charge (as in Fig. 19), and thus multiple SoH estimations may result. V-Health averages such estimations as the battery SoH during that charge. Also, there may be fluctuations among SoHs obtained from different over-night charges. V-Health uses a first-order smoother (i.e., estimating the current SoH by linear fitting current and previous raw SoH estimations) to smooth such fluctuations, and reports the smoothed result as the final battery SoH to users. Such smoothing of fluctuations is also used in the SoC estimation of mobile devices [53].

7 EVALUATION

We evaluate V-Health using both laboratory experiments and field-tests on multiple Android phones.

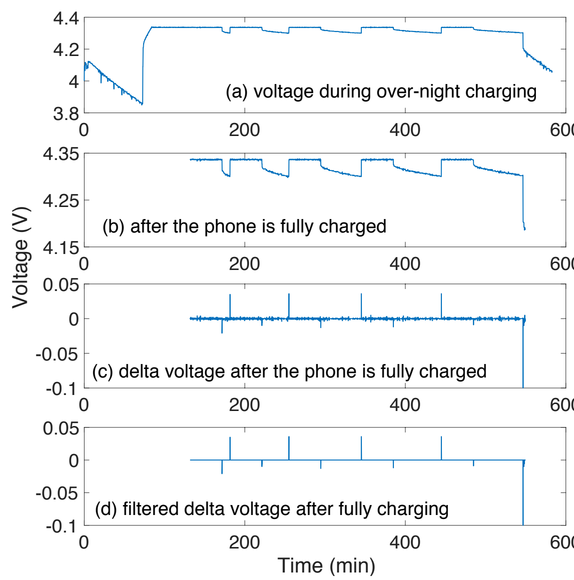
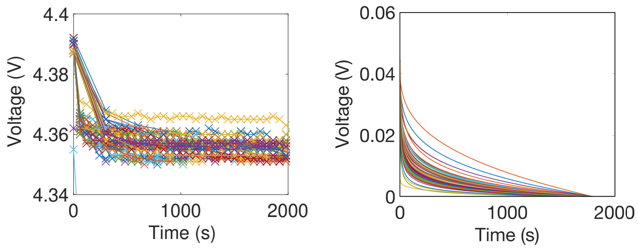


Fig. 19. Mitigating trickle charge: trickle charge pollutes the collected relaxing voltages ((a) and (b)); V-Health extracts sub-traces from the polluted trace by identifying the starting/stopping time instants of trickle charge ((c) and (d)).

7.1 Laboratory Experiments

We first evaluate V-Health based on the measurements summarized in Table 1. Relaxing voltages covering a 30-minute resting period are used as the fingerprint unless specified otherwise. For the purpose of comparison, we also implement the following three baseline methods:



(a) Raw traces **(b) Processed traces**

Fig. 20. Relaxing voltages collected on a Galaxy S5 phone: (a) raw traces after mitigating trickle charge; (b) processed traces used for fingerprint checking.

- `Casals'`: the final battery voltage after 5-min relaxation is linear in its SoH [11];
- `Bond's`: the final battery voltage after 30-min relaxation is quadratic in its SoH [10];
- `V-BASH`: the power-factor of battery voltage is linear in its SoH [20].

Note that `Casals'` and `Bond's` are not always feasible on phones for field-tests as the required voltage after a fixed-duration relaxation may not be available due to the trickle charge.

We first evaluate `V-Health` based on the dataset collected with each of the batteries, whose results are summarized in Fig. 21(a), in terms of the 5-th and 95-th percentiles of estimation errors (in absolute value) and their mean. `V-Health` estimates battery SoH with <2% mean error, and most of them are bounded by 0.5%, outperforming the three baselines in all the explored cases. More importantly, `V-Health` significantly reduces the variance in estimation error and thus is much more reliable when compared to the baseline methods.

We also evaluate `V-Health` by training the fingerprint map with a battery and validate its accuracy with the traces collected with other same-model batteries, i.e., cross-battery validation. This is the real-life analogy of estimating battery SoH of local devices based on an offline-trained fingerprint map. Fig. 21(b) plots the validation results with four Galaxy S3 and two Nexus 5X batteries, the symbol x/y denotes training with battery-x and validating with battery-y. The estimation error, albeit larger than the same-battery evaluation, is still bounded by 2% in most cases.

Users may charge their devices with different chargers from day to day, e.g., using USB or DC chargers. Next we use cross-profile evaluation to verify if `V-Health` is tolerable in such heterogeneous charger cases, with the four Galaxy S3 batteries as shown in Fig. 21(c). Specifically, we train `V-Health` with the dataset collected when charging with $<0.5C, 4.20V, 0.05C>_{cccv}$, and validating its accuracy with the dataset collected when charging with $<0.25C, 4.20V, 0.05C>_{cccv}$, i.e., with a constant charge current of $2,200 \times 0.25 = 550$mA, approximately same as when charging with standard downstream USB 2.0 ports. Comparison of Figs. 21(b) and 21(c) shows no clear evidence of degraded SoH estimation due to different charge profiles — although a few cases resulting in ≈2.5% estimation error, the errors in most cases are comparable to Fig. 21(b) and some are even smaller, verifying `V-Health`'s robustness against charger heterogeneity.

`V-Health`'s reliability can be improved further by training it with multiple batteries. Fig. 21(d) plots the SoH estimation error when training `V-Health` with three of four Galaxy S3 batteries and using the fourth one for validation, and compares it with cases of single-battery training. The results show that training with multiple batteries reduces the variance in SoH estimation and thus improves `V-Health`'s reliability, at the cost of slightly increased error as compared to the best case achieved with single-battery training. Note that such best cases, however, are rather random in terms of the battery used for training, as shown in Fig. 21(d).

We have also explored the impact of relaxing time duration and the voltage sampling rates on `V-Health`'s accuracy in SoH estimation, as shown in Figs. 21(e) and 21(f), respectively. The results show the relaxing time need not be very long, e.g., the estimation error converges with ≈10-minute relaxation, but the 5-minute relaxation in `Casal's` is not enough. Also, `V-Health` prefers higher sampling rates for fine-grained relaxing voltages.

7.2 Field-Tests on Android Devices

We have also implemented `V-Health` on multiple Android phones, including Galaxy S5, Galaxy S4, Galaxy Note 2, Nexus 6P, and Nexus 5X, and evaluated them over 4–6 months. To emulate real-life usage, these devices are discharged with various combinations of Youtube, flashlight, and an app called *BatteryDrainer* [9] that support different discharge rates, at an adaptive screen brightness, to a random SoC in the range of 0–80%. The devices are then charged for 6–10 hours (mostly over-night) during which the relaxing voltages are collected by sampling the system file `/sys/class/power_supply/battery/voltage_now`. We use additional batteries for each device module to train their respective fingerprint maps. The ground truth of the battery SoH of Galaxy S5, Galaxy S4, and Galaxy Note 2 are collected by removing the battery from the phones and fully charging/discharging them with the battery tester, with the same profile as the case of training their respective fingerprint maps. The SoH ground truth of Nexus 6P and Nexus 5X, whose batteries are not removable, is collected via Coulomb counting based on their current log during discharging, located at `/sys/class/power_supply/battery/current_now`. Although the thus-estimated ground truth may not be perfectly accurate due to the limitation of current sensing, this is the best estimation one can get as non-OEM researcher.

We first examine if the voltage-SoH relationship (as in Fig. 6) still holds on smartphones. Fig. 22 plots the voltage drop of a Galaxy S5 phone after 30-minute relaxation upon fully charged, during a period of over 5 months. Note that the voltage after 30-minute relaxation may not be available due to trickle charge, in which case we use power fitting to predict such voltage. The voltage drop increases over usage, during which the battery SoH decreases, agreeing with Fig. 6. Significant variance, however, is observed in such voltage drops, indicates methods such as `Bond's` and `Casals'` — which estimate SoH based on a single voltage reading — may be unreliable. Also, the conspicuous variance in Fig. 22 compared to those in Fig. 14 shows a clear difference between in-laboratory measurements and field-tests on mobile devices, likely due to the dynamic device operation.

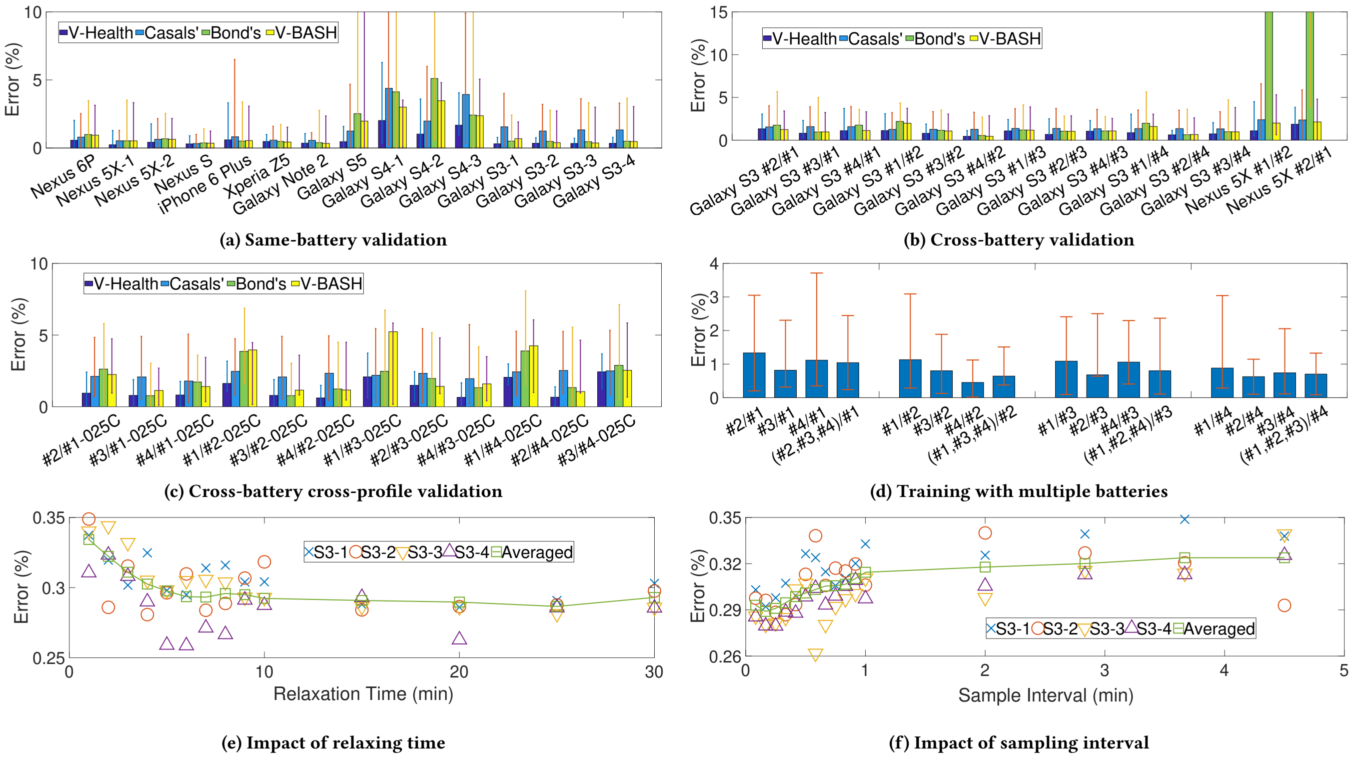


Fig. 21. Lab experiment results: `V-Health` **estimates battery SoH with** $<3\%$ **mean error and much-reduced variance ((a)-(c)); training with multiple batteries increases reliability (d); relaxing time need not be very long but has to be logged at a high frequency ((e) and (f)).**

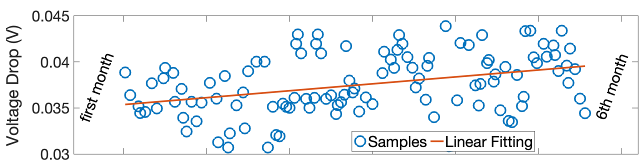


Fig. 22. Voltage drop increases over usage: the voltage drop of a Galaxy S5 phone after 30-minute relaxation increases over usage, validating `V-Health`**'s principle in SoH estimation.**

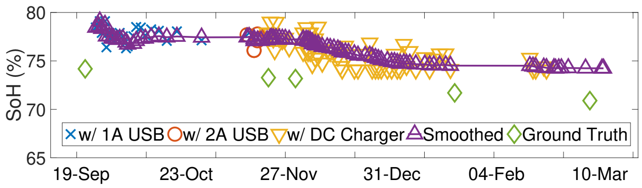
Next we check if `V-Health` can mitigate such variance and estimate SoH reliably. Fig. 23(a) summarizes the estimated battery SoH with Galaxy S5 over 6 month, together with the five ground truth SoHs measured on different dates, showing $<4\%$ errors in SoH estimation. Also, as stated above, users may charge their devices with different chargers. To cover such cases, we charged the phone with different chargers during the evaluation, namely, 1A USB, 2A USB, and its associated DC charger. No clear dependency on SoH estimation accuracy and the charger selection is observed, demonstrating `V-Health`'s robustness against heterogeneous chargers. Finally, the first-order smoother reduces the variance and thus the fluctuations of SoH reported to users, as compared to the per-charge estimations. The evaluation results with Galaxy S4 and Note 2 phones are plotted in Figs. 23(b) and 23(c), showing 1.5–4% estimation error.

Table 4: Field-test results with `Casals'`**,** `Bond's`**, and** `V-BASH`**.**

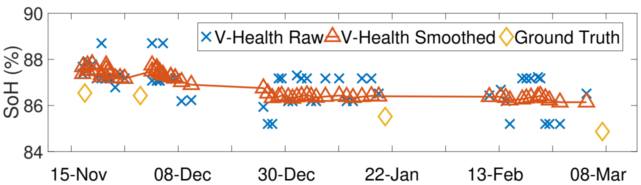
	Galaxy S5	Galaxy S4	Note 2	Nexus 6P	Nexus 5X
Casals'	52.5%	>400%	47.3%	>900%	<−1,000%
Bond's	59.3%	>1,000%	136.2%	>1,000%	>1,000%
V-BASH	63.3%	91.5%	64.4%	77.5%	118%

Figs. 23(d) and 23(e) plot the evaluation results with Nexus 6P and Nexus 5X, showing 4–5% error in SoH estimation. This relatively large error could be due partially, besides the inaccurate PMIC-provided current information, to battery's rate-capacity effect — batteries deliver more capacity when discharged with less currents [5, 37]. The two phones have an average discharge current of ≈300mA when collecting their SoH ground truth, much less than the 0.5C discharge rate (i.e., 1,725mA for Nexus 6P and 1,350mA for Nexus 5X) used in training the fingerprint maps, thus leading to the over-estimation of the batteries' full charge capacity and their SoH. Note that the first-order smoother needs at least 3 samples, causing the initial fluctuation in the smoothed SoH in Fig. 23(e).

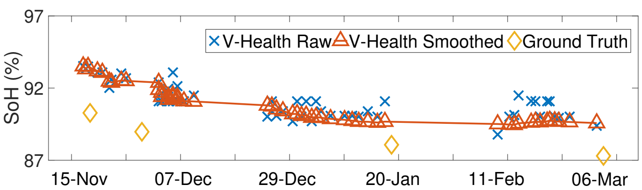
We have also tried to estimate these phones' battery SoH with the three baseline methods `Casals'`, `Bond's`, and `V-BASH` based on the same sets of collected relaxing voltages, as summarized in Table 4. Again, note that the required voltage after 5- or 30-minute relaxation may not be available due to trickle charge, in which case we use power fitting to predict such voltage and then use it to estimate SoH. The SoHs estimated by the three baseline methods



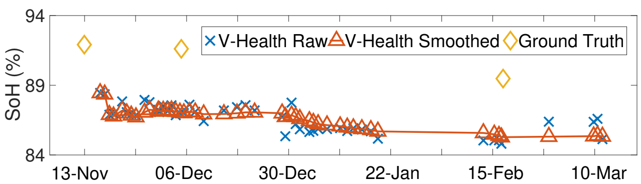
(a) Galaxy S5



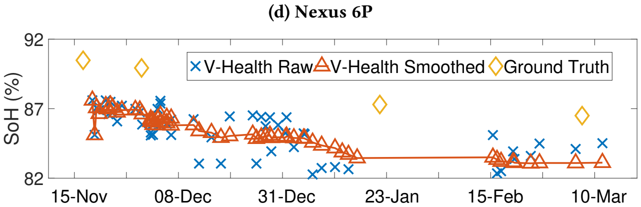
(b) Galaxy S4



(c) Galaxy Note 2



(d) Nexus 6P



(e) Nexus 5X

Fig. 23. `V-Health` estimates battery SoH with <5% error on multiple Android devices over experiment periods of 4–6 months.

have much larger error than `V-Health`, and even exceed 100% or below 0% in many cases, showing their unreliability on phones.

8 CONCLUSIONS

We have presented `V-Health`, a low-cost user-level battery SoH estimation service for mobile devices based solely on their voltage, and thus is deployable on all commodity mobile devices. `V-Health` is inspired by our empirical finding that the relaxing battery voltage fingerprints its SoH, and is steered by 50 battery measurements, consisting of 13,377 charging/resting/discharging cycles in total and lasting over 72 months cumulatively. A key takeaway from `V-Health` is the necessity to integrate physical battery properties with user behaviors in the battery management of user-centric systems such as smartphones.

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