

Accurate Capacity Estimation and Forecast of Li-ion Battery for BEV Using Telematics

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ABSTRACT

A battery traceability system that uses telematics technology was developed in order to acquire timely battery data from all FIT EVs that have been leased in the United States since 2012. The main purpose of this system is to track lithium-ion battery usage and capacity.

It has become possible to estimate battery capacity with greater accuracy than on-board Electronic Control Units by loading the time-series battery data collected from all the vehicles onto Honda servers, and applying an algorithm created to isolate the data of high accuracy from the totality of battery capacity estimation data. As a result, it was confirmed that battery capacity degradation remains within 3% in 97% of the FIT EV. It was also confirmed that FIT EV battery usage has a low frequency of remaining in the accelerated capacity degradation zone. In addition, it has been forecast by applying this data to the capacity forecast model for user patterns of usage that capacity degradation will be within 5% over the next several years.

1. Introduction

Lithium-ion battery (LIB) capacity diminishes according to battery usage and number of years of use. This has an impact on the product appeal of LIB-equipped battery electric vehicles (BEV) in terms of their driving range and other such factors. It is important, therefore, to track LIB capacity degradation in an accurate and timely manner for BEV performance evaluation when assessing trade-ins, for pricing used vehicles for sale, and so on.

Leasing of the FIT EV began in the United States in 2012. The leases were set up with a three-year lease period to start, with determination as to whether the lease period could be extended depending on a judgment based partly on the extent of LIB capacity degradation after a certain period of time. In order to extend the lease period, it would be necessary to confirm that the LIB was in a good state of health and that it had not been used in an idiosyncratic way when the LIB performance was evaluated. It would also need to be confirmed that the LIB could be expected to remain in a good state of health during the extended lease period.

With hybrid electric vehicles (HEV), the usage and state of performance of the on-board LIB previously was collected by means of the Honda Diagnostic System (HDS).

Under this method, usage data picked up by on-board sensors and estimated LIB capacity data from the on-board Electronic Control Unit (ECU) were stored in the ECU. That stored data was then collected by the HDS at Honda dealers during vehicle inspections and other such occasions that occur at irregular intervals. The collected data was transmitted to Honda servers, where it has been analyzed and utilized.

However, there were three issues with the method of collecting data by means of HDS for judging extension of the lease period. The opportunities to collect data are limited to when vehicle inspections and other such occasions occur, so that data cannot be analyzed and utilized in a timely and comprehensive manner. The on-board ECU on an HEV is used to estimate LIB capacity primarily for the purpose of fault determination. Consequently, it does not have the accuracy of capacity estimation needed to evaluate the influence on driving range, which is crucial for the BEV in a way it is not for vehicles that do not depend exclusively on batteries for power. Moreover, future capacity forecast requires the accumulation of vast amounts of data on usage and high-load computation of future capacity based on that usage. Given the allowed mounting space and cost constraints on the on-board ECU, however, dealing with the above issues was challenging. In order to resolve these

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issues and collect data without imposing any burden on the user, it was decided to make use of telematics technology, which Honda is already deploying as a service.

2. Development Goals

It was determined that a new system to collect, store, and analyze BEV LIB data would be needed in order to resolve the issues in the previous chapter. The following three points were taken as the main goals:

- (1) To be able to collect, analyze, and utilize usage and changes in LIB capacity in all vehicles in a timely manner without additional burden on users;
- (2) To be able to make a more accurate estimation of LIB capacity than the ECU estimated value; and
- (3) To be able to forecast future changes in LIB capacity in accordance with individual vehicle usage.

3. Flow of LIB Data Utilization

The quantity of LIB-related time series data that is collected while a FIT EV is traveling and while it is charging is enormous. There was concern that, when analyzing an enormous amount of data, the intended analysis results could not be efficiently obtained if collection and analysis of the data was begun before the issues and the flow for resolution of issues had been defined. In building the data collection system, therefore, the aim was to clearly define the issues and create an LIB data utilization flow (Fig. 1) intended to efficiently collect, analyze, and utilize LIB-related data.

In order to collect data on approximately 1,000 FIT EV without any burden on users or dealers, a battery traceability system was developed to make use of the telematics system⁽¹⁾ already being deployed for service in the United States.

Data collection involves gathering time series data on every FIT EV in the United States in a timely fashion after the users' consent has been obtained. Raw data on the vehicle and LIB while traveling and while charging is transmitted as time-series binary data by means of the on-board telecommunications unit (Telematics Control Unit: TCU) and the mobile telephone network. The transmitted data is accumulated on Honda servers. The accumulated

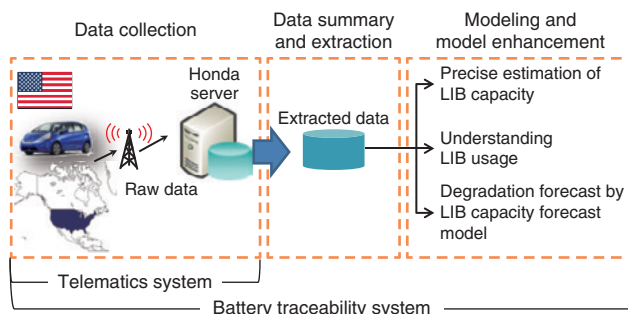


Fig. 1 LIB data utilization flow

data is intermittently converted to text data and summarized as per single drive and per single charge data sets. This allows a comprehensive grasp of usage for all the vehicles. Data relating to highly accurate estimation of LIB capacity, analysis of usage, and capacity forecast is extracted from the summarized data and a model for analyzing it is created. As the person performing analysis inputs the data to the model, the model is modified and made more accurate in the process. Capacity estimation and capacity forecast are high-load computation processes, and these are implemented on the server side with the aim of achieving estimation of capacity and forecast of changes with a greater accuracy than the ECU. The capacity forecasting makes use of the LIB Capacity Forecast Model⁽²⁾ that was created in parallel with the FIT EV development.

4. Highly Accurate Capacity Estimation

4.1. On-Board ECU Capacity Estimation Method

LIB capacity is sought from the integration of current (ΔAh) divided by the displacement (ΔSOC) in the LIB charging rate (State Of Charge: SOC) during the same period by linear regression (Fig. 2) using the sequential least square method⁽³⁾. This is shown in Eq. (1).

$$Capacity = \frac{\Delta Ah}{\Delta SOC} \quad (1)$$

When this is done by the on-board ECU, ΔAh is calculated by integrating the electrical current values from on-board electrical current sensors.

On the other hand, SOC is a physical quantity that cannot be observed directly by on-board sensors. Therefore it has to be estimated, and there are two general methods for doing this. In the first method, the open circuit voltage (OCV) at the LIB terminals is first estimated. Then the SOC-OCV curve (the SOC-OCV relationship unique to the LIB) is used to convert OCV to SOC. This is the OCV

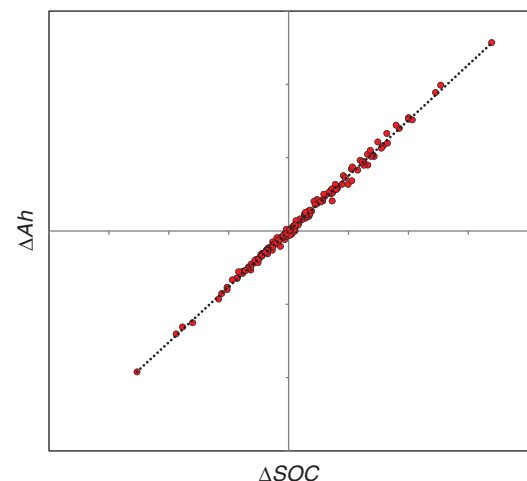


Fig. 2 Recursive least square method for capacity estimation

estimation method (Fig. 3).

The second method uses the integration of current and LIB capacity to estimate the SOC change from when the vehicle initially started traveling. This is the current integration method.

4.2. Capacity Estimation Error of the On-Board ECU

With the OCV estimation method, an OCV estimation error occurs when the battery is loaded, because OCV cannot be directly observed in this condition. When OCV is converted to SOC, therefore, the OCV estimation error influences the SOC estimation error (Fig. 4).

On the other hand, the current integration method involves a measurement error of several percentage points in on-board current sensors. That error therefore becomes cumulative with the passage of time, and the SOC estimation error grows larger.

Whichever of the above two methods is used, the estimated SOC will contain an error, and therefore error will also occur in the LIB capacity estimation. Figure 5 shows the change over time in LIB capacity estimation by the on-board ECU as a percentage of the LIB capacity true value, which is 100%. During approximately 4,000 seconds of travel, ECU estimation capacity has an error of about $\pm 10\%$ relative to the capacity true value. This capacity estimation error presents an issue in that it means LIB capacity degradation cannot be tracked with high accuracy by the on-board ECU.

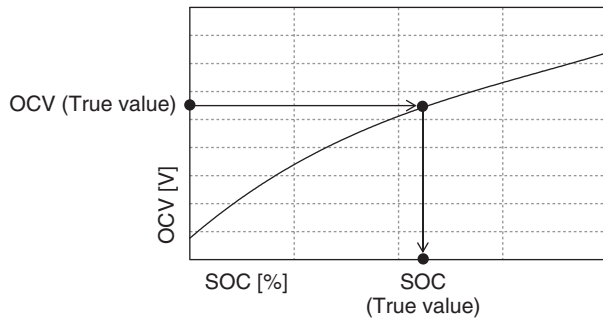


Fig. 3 Conversion of OCV to SOC

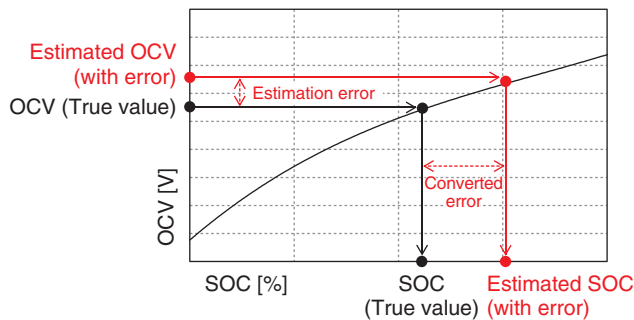


Fig. 4 Conversion of estimated OCV with error to SOC with error

4.3. Highly Accurate Method of Capacity Estimation Using Servers

In order to deal with the error with respect to capacity true value, the possibility of building a model to use the enormous quantity of time-series data accumulated on the servers to calculate capacity with a high degree of accuracy was examined.

In setting a target for capacity estimation accuracy, it was assumed that a 10% decrease in driving range would affect driver usability. Considering this assumption and taking into account that LIB capacity would diminish, the target tolerance was set at $\pm 6\%$ or less.

When creating the model, the notion was conceived that just the data for travel where capacity estimation error is smaller (where estimation accuracy is greater), or where data is for charging conditions only, could be extracted from all travel and charging data. Therefore, various travel and charging conditions were examined in order to extract those conditions with greater estimation accuracy. As a result, it was found that greater estimation accuracy could be obtained under the following two conditions.

The first condition was that where ΔSOC is larger (travel distance is longer), the capacity estimation accuracy becomes greater. Figure 6 shows ΔSOC on the horizontal axis and the capacity estimated by the ECU on the vertical axis. As

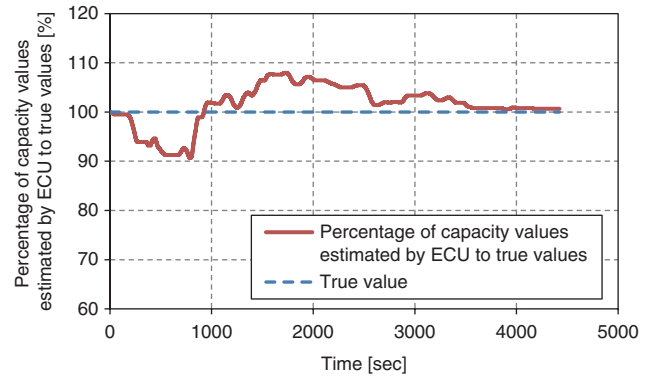


Fig. 5 Variation in capacity values estimated by ECU

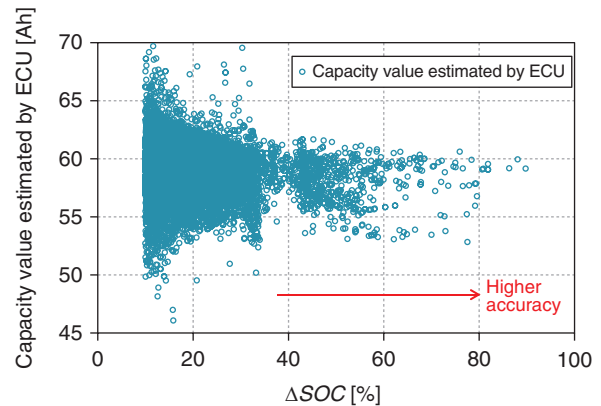


Fig. 6 Used range of SOC and variation in capacity estimation

the ΔSOC becomes larger, the true value of capacity tends to converge on 60 Ah.

The second condition was that when an adequate rest period is included after travel or charging, such that when capacity estimation also includes the rest period, the estimation accuracy becomes greater. The reason for this, as shown in Fig. 7, is that capacity estimation accuracy is greater when an SOC figure obtained from an OCV that has become stable after adequate rest is used rather than an SOC figure calculated by the ECU when travel has ended. Consequently, capacity was calculated using a period that includes rest, by selecting from the collected time-series data those items of travel or charging data linked with extended rest data.

When data meeting the above two conditions was extracted from the total quantity of data collected, it was confirmed that, as envisioned, the extracted sample provided greater estimation accuracy. A new issue then emerged, however, because it was found that the greater the estimation accuracy became, the smaller the number of vehicles became that could be used for capacity estimation (Fig. 8).

This is because, as a matter of user patterns of usage, there is a lower frequency of long-distance travel (travel

with a larger ΔSOC). In order to achieve the target error tolerance of $\pm 6\%$, data for ΔSOC 30% and greater has to be extracted. In this case, however, the vehicle coverage (the percentage of vehicles that can be calculated with a target error tolerance within $\pm 6\%$) ends up dropping to 78%, with the result that 22% of vehicles could not have their capacity estimated with great accuracy.

4.4. Increasing Vehicle Coverage

The approach conceived to resolve the issue of reduced vehicle coverage was to connect individual travel data items to create a new travel pattern with larger ΔSOC . The multiplicity of travel ΔAh and ΔSOC values that could be connected to satisfy the rest time condition for data extraction were connected to form single data sets. These data sets were then used for capacity estimation (Fig. 9).

Performing capacity estimation in this way by connecting travel history data make it possible to achieve a balance between greater estimation accuracy and increased vehicle coverage. Connecting travel history data with ΔSOC of 20% or greater can achieve accuracy within the target error tolerance together with vehicle coverage of 97% or greater (Fig. 10).

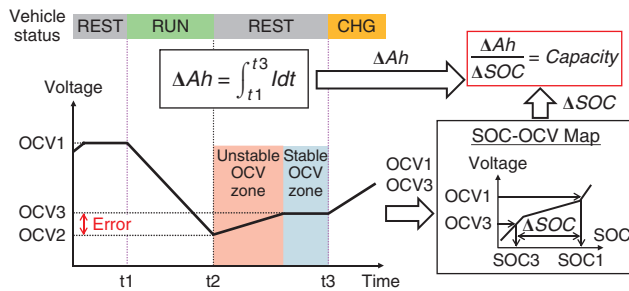


Fig. 7 Method for capacity estimation with battery traceability data

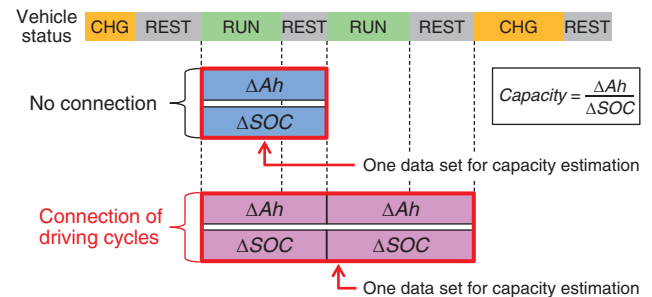


Fig. 9 Connection of driving cycles for precise capacity estimation

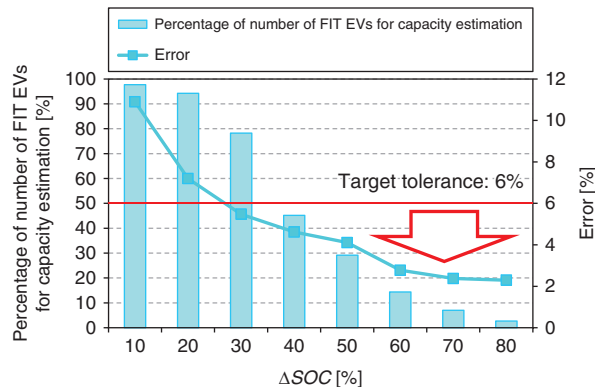


Fig. 8 Number of EVs with accurate capacity estimation and estimation error to used ranges of SOC

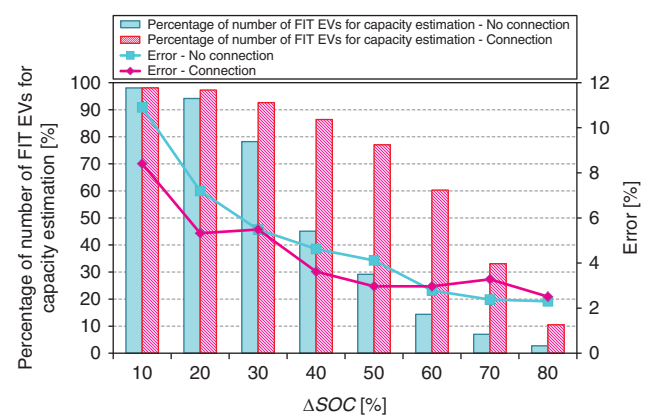


Fig. 10 Enhancement of vehicle coverage and estimation error

4.5. Results of Capacity Estimation

Figure 11 is a graph with LIB capacity of 805 FIT EV units for the United States market estimated using this capacity estimation method at 10,000 km travel intervals. The capacity estimation error margin and frequency are shown in a box plot graph. The areas with darker color indicate greater sample density, and lighter color indicates lower sample density. In order to verify the accuracy of this capacity estimation method, the LIB packs were removed from four FIT EV units that include the above durability tested vehicles, and their LIB capacity was measured using the LIB charge and discharge test system with highly accurate electrical current sensors. The actually measured capacity values were located along the interpolation line and extrapolation line for median capacity value calculated by this capacity estimation method. It was found that the accuracy of this capacity estimation method and the LIB capacity degradation do not diverge by more than 3%.

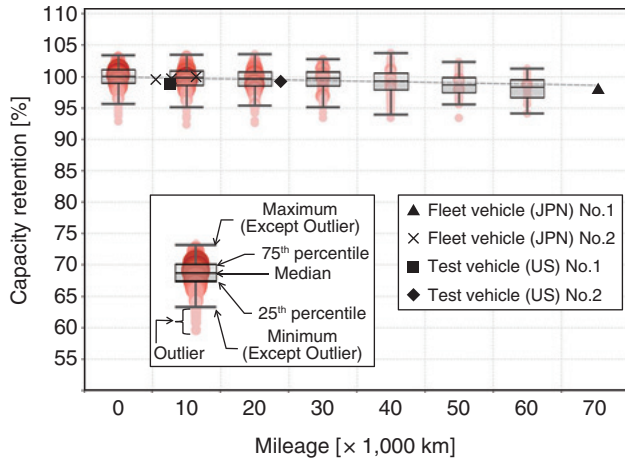


Fig. 11 Estimated FIT EV capacity

5. Changes in LIB Capacity

5.1. Capacity Degradation Acceleration Conditions

The factors that accelerate LIB capacity degradation are generally said to include LIB temperature, charge and discharge current values, and usable SOC (voltage) width⁽⁴⁾.

The LIB for the FIT EV was subjected to cycle durability testing with the above factors varied. This bench testing confirmed the extent of acceleration of capacity degradation under the various conditions.

Figure 12 shows the results for examination of the influence of temperature by fixing the current during charge and discharge at 20 A and the width of SOC from 100% to 0% while the LIB temperature is varied at the four levels of 25°C, 35°C, 45°C, and 55°C. It was found that the capacity

degradation is accelerated at higher LIB temperatures, with conspicuous capacity degradation observed at 55°C and above, in particular.

Figure 13 shows the results for examination of the influence of SOC width during charge and discharge on capacity degradation by fixing the current during charge and discharge at 20 A, the LIB temperature at 35°C, and SOC at the start of discharge at 100% while only the SOC at the end of discharge is varied at the four levels of 0%, 40%, 70%, and 85%. Conspicuous capacity degradation was observed when SOC at the end of discharge was 0%.

Figure 14 shows the results for examination of the influence of current on capacity degradation by fixing the LIB temperature at 35°C and the width of SOC from 100% to 0% during charge and discharge while varying the current

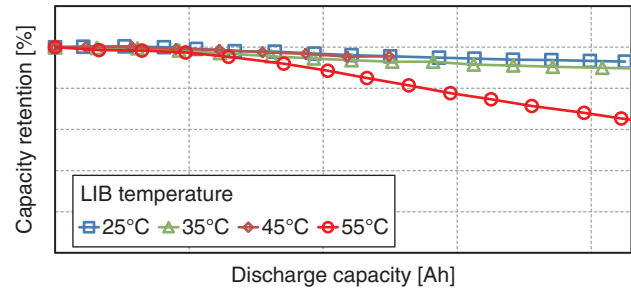


Fig. 12 Durability test with LIB temperature as parameter

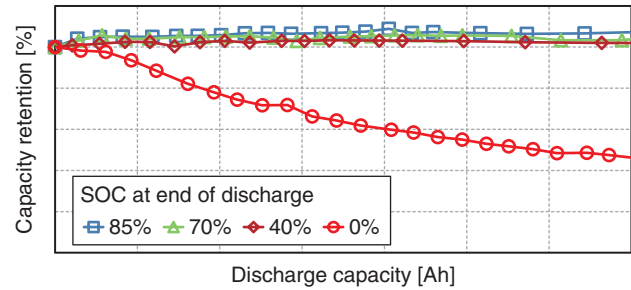


Fig. 13 Durability test with width of SOC window as parameter

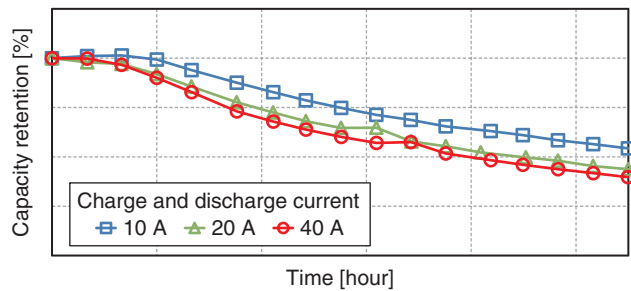


Fig. 14 Durability test with current as degradation parameter

at the three levels of 10 A, 20 A, and 40 A. It was found that increasing the current caused acceleration of capacity degradation by a very slight amount, but it was confirmed that no conspicuous tendency, as seen with temperature and width of SOC, was to be observed.

As explained above, the result of durability testing conducted under various conditions was that the extent of capacity degradation could be grasped quantitatively in terms of the three factors of temperature, SOC at the end of discharge, and current.

Given an environment of use by the user, when the frequency of entry into the accelerated capacity degradation zone of these factors was higher, LIB capacity degradation was anticipated to advance more conspicuously.

5.2. Influence on LIB from Usage Analysis

In each of the accelerated capacity degradation zones confirmed in the previous section, the frequency of LIB use was studied using the data from 580 vehicles with a record of driving for one year or more from the start of leasing.

As shown in Fig. 15, confirmation of the maximum LIB temperature frequency during traveling and charging showed that the frequency in the accelerated capacity degradation zone of 55°C or higher was virtually zero.

Confirmation of the frequency distribution (resolution 5%) of SOC at start of charge shows that SOC from 55% to 60% is the most frequent value. The frequency of remaining in the accelerated capacity degradation zone (SOC 0% to 5%) was the lowest of all zones at less than 3.8% (Fig. 16).

Figure 17 confirms the frequency of current during travel and charging. The peak near zero represents the supply of electric power for system operation. If this is removed, the graph more or less has the shape of normal distribution. On the regeneration side (in the negative zone), it does not remain in the accelerated capacity

degradation zone, and on the discharge side, there is a higher frequency of remaining than on the regeneration side, but no conspicuous difference in frequency was observed.

The frequency of remaining in the zone was 3.8% only in the accelerated capacity degradation zone for width of SOC, and the frequency of remaining in other accelerated capacity degradation zones was nearly zero. Considering that the frequency of remaining in these three accelerated capacity degradation zones was generally low, the influence of usage by users on the acceleration of LIB capacity degradation could be said to be slight. The usage analysis results confirm that the FIT EV experiences little reduction in LIB capacity.

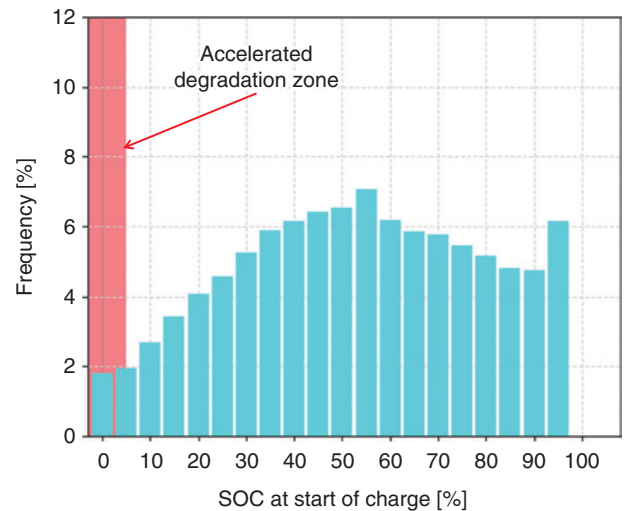


Fig. 16 Frequency distribution of SOC at start of charge

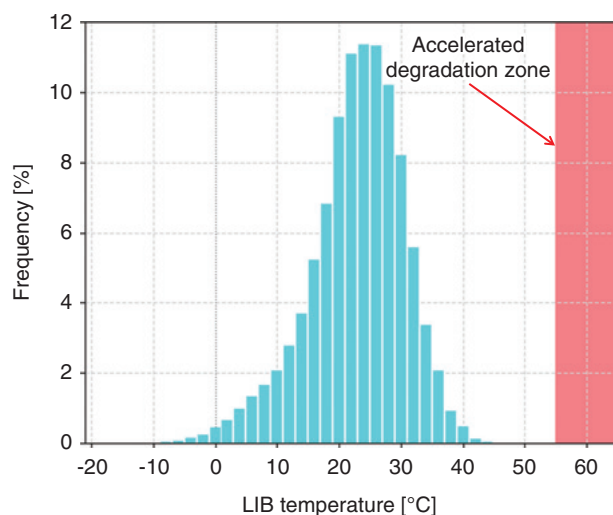


Fig. 15 Frequency distribution of battery temperatures

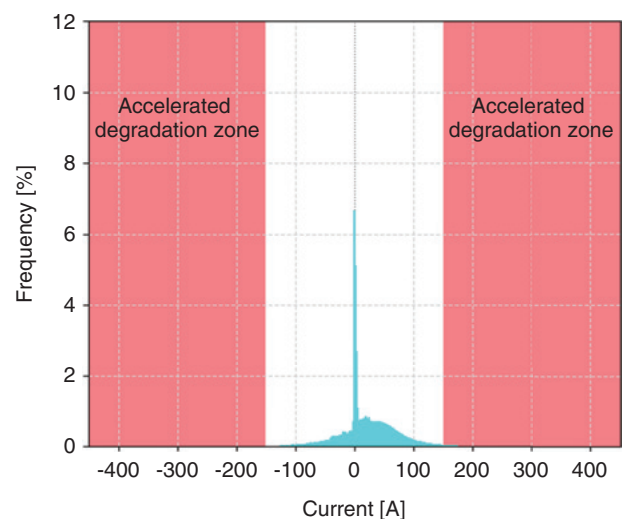


Fig. 17 Frequency distribution of battery current

5.3. Capacity Forecast

It was reasoned that future LIB capacity forecasting is important when judging whether to extend a lease period. Therefore, the LIB usage data for the most recent year from 682 vehicles was plugged into the LIB Capacity Forecast Model⁽²⁾ vehicle by vehicle, and the capacity was tentatively forecast for the case of the same usage being repeated again in the future. The result was a forecast that even if the lease period were to be extended, LIB capacity degradation would remain at or under 5% during the lease period (Fig. 18).

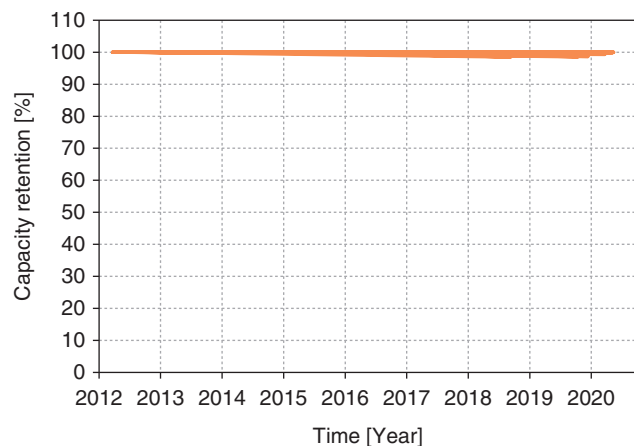


Fig. 18 Forecasted capacity degradation

6. Conclusion

A battery traceability system based on telematics technology was created and yielded the following results.

- (1) A highly accurate capacity estimation method was established that satisfies the requirements of a target accuracy tolerance within $\pm 6\%$ and vehicle coverage of 97% or greater. This method confirmed that LIB capacity degradation in the FIT EV remains within 3%.
- (2) It was confirmed that LIB usage in the FIT EV has a low frequency of remaining in the accelerated capacity degradation zone.
- (3) When usage by users was plugged into the capacity forecast model and capacity was forecast, capacity degradation was forecast to remain within 5% during the period of the lease that is to be extended.

There were requests from users for extension of the lease period, and since the good state of health of the LIB was verified as described above, the American Honda Motor Co., Inc. announced on March 23, 2015 that it would extend FIT EV leases by two years.

References

- (1) Takemasha, K., Uchida, T., Tsurutani, T., Tominaga, Y., Satoh, K.: Development of Battery Traceability System

for EV, Honda R&D Technical Review, Vol. 25 No. 1, p. 36-41

- (2) Tominaga, Y., Kawamura, M., Takemasa, K.: Creation of a Model of Battery Capacity Degradation Reflecting Battery Internal States, the 54th Battery Symposium in Japan, p. 101, (2013)
- (3) Maruno, N., Komoda, S., Nishida, Y.: Battery Control Technology of Li-ion Battery System for HEV, Honda R&D Technical Review, Vol. 24 No. 1, p. 76-81
- (4) Ichimura, M.: A Study of Life Characteristics of Small Lithium-Ion Batteries, NTT Building Technology Institute 2005, p. 1-7, (2005)

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