Cloud-connected Battery Management System Supporting e-Mobility

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Electric vehicles have evolved along with a reduction in the size and weight of batteries. This has led to the development of bicycles, motorcycles, and small vehicles suitable for short distances that are driven by batteries small enough to be replaced by the user. Once batteries become readily replaceable even when away from the home or office, problems such as lengthy charging times and limited running distances will be overcome, and the practicality of electric vehicles will further increase. Since it would be difficult for users to carry replacement batteries with them or to store them at convenient locations, a battery-sharing system is essential. Fujitsu aims to establish a mechanism for grasping the status of shared batteries that will enable users to replace batteries with peace of mind and with no perceived degradation in battery quality. This cloud-connected battery management system will maximize the value of the shared batteries by using a location data cloud to continuously connect to the batteries, manage the state of their charge, and monitor changes in their characteristics. This paper presents the technology to be used to achieve this system and discusses how it will create new value.

1. Introduction

It is said that the reduction of CO_2 emissions is a matter of urgency as a countermeasure to global warming and that the powering of vehicles by electrical means is essential. However, a number of problems would arise if electric vehicles (EVs) were made that could cover the same distances as gasoline-powered vehicles. For example, the battery would be about half the weight of the vehicle, the charging time would be long, and the charging facilities would be large in scale.

EVs include electric bicycles and electric scooters used mostly for short distances. These types of vehicles can be made using relatively compact and light batteries that can be easily recharged and/or replaced at home, and they have found widespread use as a result. In addition, the acceleration performance and running distances of some EVs are finally reaching the point where the EVs are practical.[1)]

If an EV is run until the battery is almost fully discharged, the battery must be quickly recharged or replaced with a charged battery. As batteries evolve and energy density increases, it will be necessary to ubiquitously deploy more powerful charging facilities or implement a system for replacing discharged batteries with charged batteries. The latter alternative is obviously more cost effective.

As an information technology company, Fujitsu aims to create a mechanism for handling battery-related information essential to achieving such a battery replacement system that will push e-mobility into a new stage. This paper describes the key concepts and technologies for achieving an "e-mobility society."

2. Battery replacement system for small EVs

Most everyday driving is done to go shopping or perform errands. In other words, cars are generally used for short rides on a nearly daily basis. The distance traveled per trip is considered to be about 10–20 km in Japan (meaning an average running distance per month within 300 km[2)]). These usage conditions mean that EVs can be given a compact configuration with a battery module that is relatively small and light and replaceable as well. With this in mind, we envision the following usage scenario for EVs: in addition to providing facilities to charge batteries that are running low on power, charged batteries can be placed at key locations throughout a community so that discharged batteries can be replaced with charged ones as needed. This scenario corresponds to a new way of using EVs as part of an e-mobility society.

The following summarizes a battery replacement system applicable to an e-mobility society.

1) Small and light replacement batteries for use in an e-mobility society

Batteries that are small enough and light enough to be replaced manually by the user are needed to establish a battery replacement system. Three sizes are envisioned for a vehicle-mounted lithium-ion battery.

- 1 kWh (8–10 kg): size of a briefcase
- 2 kWh (15–18 kg): size of an airplane carry-on bag
- 4 kWh (30–36 kg): size of a golf bag

Even the largest of these three sizes (4 kWh) falls within the range of batteries that can be manually replaced. As for the size of vehicles that can be driven by these lithium-ion batteries, a 1-kWh battery can drive vehicles from a two-wheeled moped to those having power close to that of a three-wheeled scooter in the 125-cc class, and a 4-kWh battery can drive a three- or four-wheeled lightweight vehicle.

2) Reduction/Elimination of facility investment

Storing charged batteries or installing charging lockers within the service area of a battery replacement system (a "cloud-connected battery management system") enables the construction of power stations in accordance with demand without having to make a major investment. While the rental of EVs in sightseeing areas or at tourist attractions can be treated as a form of business based on EVs, demand can fluctuate in no small way on weekends, by the season, or when events are being held. A cloud-connected battery management system is the most practical way to deal with such fluctuation in a flexible manner with the lowest cost and thereby promote the spread of the e-mobility society.

3. Technologies for managing battery information toward e-mobility

To make e-mobility practical, it is essential that the driver of an EV be accurately informed of the battery's remaining charge and the remaining distance that the vehicle can travel. In this section, we introduce Fujitsu's approach to making more accurate predictions of an EV's running distance. We examine battery-replacement technologies for small EVs while referring to experimental data on remaining charge, i.e., state of charge (SOC), and EV running data for existing standard-size EVs and light EVs.

3.1 SOC and running distance

To gain a better understanding of the present state of EVs and batteries, we performed an experiment using a commercially available Japan-manufactured EV. In this experiment, we attempted to drive up a mountain road with four adult passengers on a clear day in spring with the air conditioner set to "light." This uphill road had a maximum slope of 8.8%, and at the start point of the course (foot of the hill), the vehicle indicated a predicted running distance of 60 km. Since the actual driving distance for this experiment was set to about 9.5 km, this value represented a considerable margin of about six times, which was initially thought to be more than sufficient. In actuality, however, the predicted running distance decreased about 1 km every 100 m or so, which meant that power was being consumed about ten times faster than when driving on level ground. Nevertheless, by turning off the air conditioner along the way and continuing on, we eventually made it up the mountain with more than 10 km of predicted running distance to spare but not without some anxiety.

In other words, the predicted running distance with this EV fluctuated greatly, and a sense of unease began as soon as the SOC dropped by more than half and the predicted value fell below 60 km. Of course, gasoline-powered vehicles also suffer from degraded fuel consumption on an uphill road, but with a 10-L reserve tank and fuel consumption of 5–10 km/L, the ability to drive an additional 50–100 km alleviates any concerns. In short, the situation for gasoline-powered vehicles differs from that for EVs in terms of distance margin.

A detailed comparison of EVs and gasoline-powered vehicles shows that the energy efficiency of internal combustion engines is 20–30% while that of electric motors is 70% or greater, which means that the energy efficiency of EVs is about three times that of gasoline-powered vehicles. An EV is also capable of energy regeneration during deceleration, recovering about twice the amount of energy used by a gasoline-powered vehicle. As a result, an EV can be driven by 3–5 times less energy than a gasoline-powered vehicle in total.

However, the energy needed to run an air conditioner is the same in both cases, so if fuel consumption worsens by 10% when using air conditioning in a gasoline-powered vehicle, power consumption would worsen by 30–50% in an EV. Apart from this, the effect of weight such as that of passengers and luggage is related to vehicle weight. For small EVs and e-bikes, for example, the effect on power consumption can double to the extent that adding one passenger can degrade power consumption by 10–30%. These deteriorations in power consumption are not as bad as that caused by driving on an incline, but they must be taken into consideration.

The constituent elements of the equation "running distance = SOC × full charge energy [kWh] / power consumption [kWh per km]" are shown in **Figure 1**. Both SOC and power consumption are dependent on many parameters that can fluctuate widely, making them difficult to use.

Furthermore, while improvements can be made to some of these constituent elements, obtaining an accurate understanding of SOC and the state of health (SOH), which indicates the degree of SOC degradation, is basic to this effort. An accurate SOC value is also essential to vehicle control.

3.2 Life Expectancy Visualization (LEV) technology

The battery of an EV undergoes discharging and charging during a trip, resulting in current that can fluctuate in a very complicated manner. This current acts on internal resistance, generating complicated drops and rises in voltage. As a result, the voltage, current, and temperature data measured at the battery terminals can differ greatly from static characteristics obtained in the laboratory. In addition, heat generation can significantly alter characteristics. Thus, attempting to determine exactly how much charge is left from either a chemical-reaction or electrical perspective by measurement alone is futile. What is needed, rather, is procedure-based, full-scale corrective calculations technology. To this end, we have developed LEV technology, which can estimate with high accuracy a battery's SOC and SOH through corrective calculations and compute the battery's degree of degradation.

The flow of SOC and SOH calculation is shown in **Figure 2**. The first step in this process is to perform a corrective conversion to estimate the terminal open circuit voltage (OCV) with the effects of internal resistance

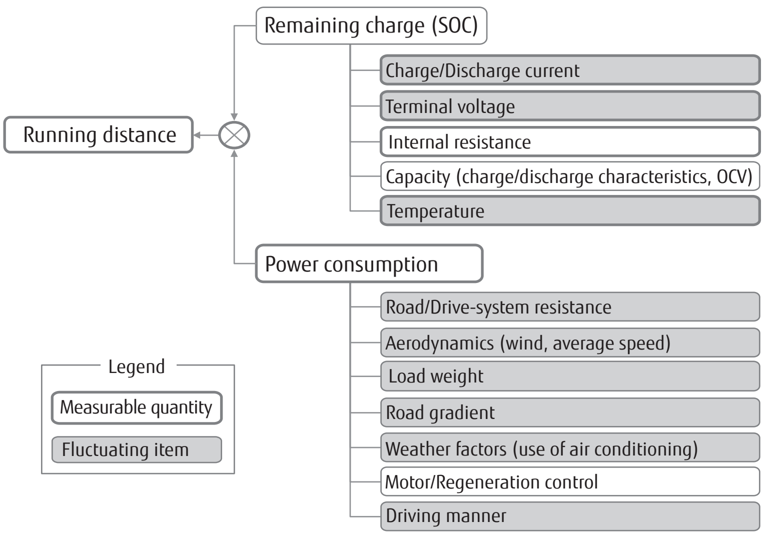

Figure 1
Constituent elements of "running distance = SOC × power consumption."

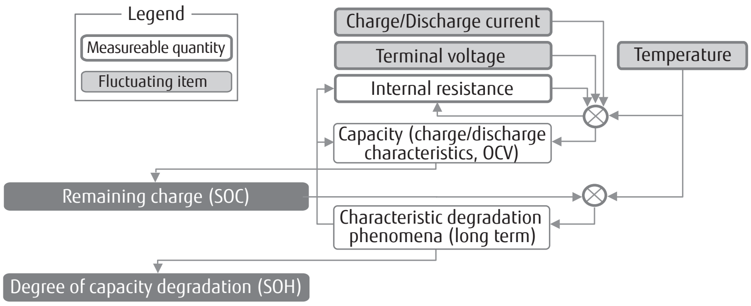

Figure 2
Flow of SOC and SOH calculation.

and current variation removed. This conversion makes use of battery characteristic data (internal impedance, full charge capacity, temperature variation, etc.) obtained beforehand. The relationship between OCV and SOC is also measured beforehand as characteristic data for each battery, and SOC is estimated from OCV using statistical processing, look-up tables, or other techniques. In lithium-ion batteries, the change in OCV with respect to a change in SOC is small, so it is easy for an error to appear in the SOC estimation calculation. In addition, these characteristic data vary from battery to battery and can be affected by heat and usage conditions. In short, it is exceedingly difficult to minimize estimation error solely on the basis of this technique.

Another method for estimating SOC is Coulomb counting. In this method, however, the error associated with the current sensor and the error resulting from the inability to completely track current variation in a realistic measurement interval are accumulated and magnified. Thus, sufficient accuracy cannot be obtained with this method either.

The basic concept of the SOC estimation algorithm in the LEV technology that we developed is as follows. The SOC value obtained by OCV conversion in real time is progressively revised using the two SOC calculation methods described above: one based on OCV conversion and one based on Coulomb counting (including errors). Convergence calculations applying the Kalman filter (KF) algorithm are used for estimating the state of a dynamic system using measured values having error. In the conversion to OCV from terminal voltage, we use a simple resistor-capacitor equivalent circuit to reproduce the transient characteristics of voltage accompanied by current variation. While this model cannot fully reproduce battery characteristics, it is sufficient for estimating SOC with a somewhat small amount of error. In the model, the basic approach is to perform short-term calculations of SOC while trusting the values obtained by Coulomb counting and to then revise as needed whenever the error generated is deemed to be large on the basis of the converted OCV. Which of the OCV and Coulomb counting methods to trust and give priority to can be adjusted by setting the KF parameters. Additionally, to deal with error resulting from the incompleteness of the battery model for performing OCV conversion, we incorporated a mechanism for suppressing correction based on OCV conversion during times in battery operation when the effects of such incompleteness are prominent. This strategy prevents an infinite accumulation of error.

With reference to the “Guidelines for Converted Electric Vehicles,” published in 2011 by the Association for the Promotion of Electric Vehicles, the results of estimating SOC by simulation are shown in **Figure 3**. They are based on JC08-mode measurement data for an EV converted from a commercially available Japan-manufactured light automobile. For this simulation, we used a lithium ion battery using iron phosphate for the positive electrode. Among lithium ion batteries, this type is particularly prone to error in estimating SOC since the change in OCV is especially small with respect to a change in SOC. Nevertheless, our LEV technology estimated the SOC with a high level of accuracy (maximum absolute error under 2%; average absolute error under 1%).

The SOH is estimated on the basis of battery usage conditions (charge/discharge state: SOC, voltage, current, temperature). Typical of degradation phenomena in which battery capacity decreases are a degradation mode determined by SOC and temperature (shelf

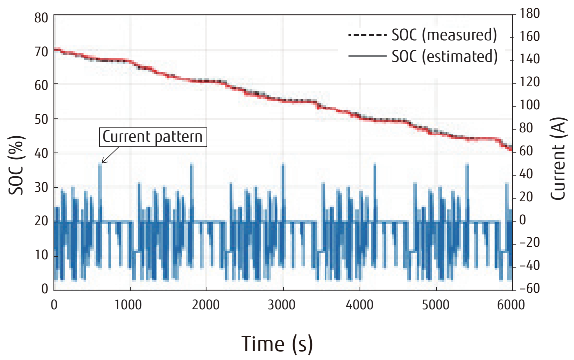

Figure 3
SOC simulation results.

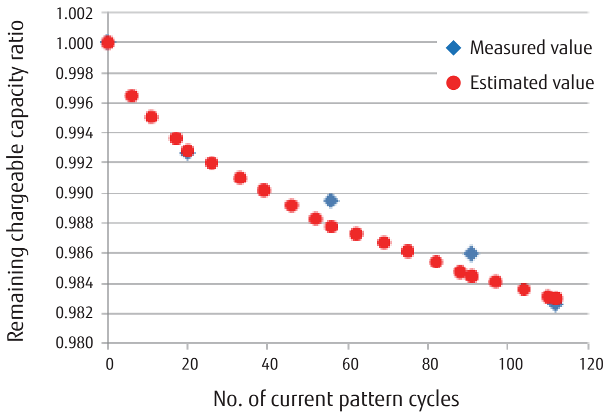

Figure 4
SOH simulation results.

mode) and a degradation mode determined by accumulated current and temperature (current degradation mode). For each of these modes, the relationship between the speed of degradation and the parameters can be obtained beforehand as characteristic battery degradation data. Temperature, in particular, is an important parameter for both modes. It is the battery's internal temperature out of which degradation phenomena actually arise, and it can change from moment to moment. In an actual system, a battery's internal temperature cannot be directly measured, so we devised an algorithm for estimating it on the basis of the charging status and external temperature and incorporated the algorithm in our LEV technology.

The results of estimating capacity degradation by using LEV technology when applying envisioned current patterns continuously for two months and performing observations are shown in **Figure 4**. The actually measured change-in-capacity could be reproduced well by fitting internal-temperature estimation parameters against battery-degradation characteristic data obtained beforehand.

It is therefore possible to estimate SOH in the above way by using LEV technology. However, in reality, the battery degradation characteristics can suddenly change, preventing such estimation from being performed. We can improve responsiveness to the battery's actual SOH by using SOH estimation as a supplement to gauging degradation through actual measurements of battery capacity.

3.3 Power consumption as an uncertain index

Once SOC is obtained, it would appear that the running distance could be estimated from SOC and average power consumption, much as fuel consumption is used to determine running distance in a gasoline-powered vehicle. In actuality, however, this method cannot be used because the result could be too uncertain, which would create an element of risk. Unlike a gasoline-powered vehicle, there is no margin of energy reserves; moreover, energy regeneration, the key power saver, is highly variable because it depends on the driving style and traffic conditions. It takes only an approaching hill to throw off the power consumption calculations by an order of magnitude. Power consumption is also sensitive to air conditioning use, headwinds, fluctuating vehicle loads, etc.

In short, a good index in the form of "actual average power consumption" cannot be created. A better approach is to clarify reachability; that is, "can the vehicle reach its destination?" It is more important to display an indicator such as "destination is definitely reachable" than "power consumption value." This holds true for the e-mobility society that we envision.

Given that the effects of an uphill stretch of road can be significant, we considered it essential that map data be incorporated in LEV technology and decided that an EV should be connected at all times to a location data cloud by wireless means. This makes possible various types of driver support such as color-coding of a map screen to show the vehicle's definite driving range and/or the range that could be achieved by eco-friendly driving techniques. Providing such support can contribute to a more convenient and stress-free e-mobility society.[3)]

4. Calculation of running distance on the cloud

The process flow for calculating running distance is shown in **Figure 5**. The value of distance traveled divided by the amount of power consumed, that is, the rate at which power is being consumed (power consumption), includes a variety of elements, making prediction difficult. On the other hand, actual measurement is simple.

For this reason, we begin by measuring power consumption at fixed intervals. Then, by comparing those measurements with GPS and map data, the effects of road gradients can be well understood. For example, once average power consumption values have been obtained for flat interval A, uphill interval B, and steep-uphill interval C, they can be compared, and physical formulas can be used to determine the relationships between power consumption and road rolling resistance, road gradient, etc. These results can be recorded, so fairly accurate running-distance predictions can be calculated when traveling on the same routes. The same results can even be used for predicting running distance on roads with different gradients. In this regard, we investigated the continuous connection of batteries to a location data cloud and the application of big data processing using the following techniques as a new approach to predicting running distance.

1) Actual measurement of data + table look-up

This technique collects a huge volume of actual driving data for diverse parameters such as vehicle type, weight, and speed, temperature, wind speed, road gradient, and road interval and forms a database consisting of look-up tables. It predicts running distance by interpolating between actual measurements. This technique, though simple in concept, is not considered to be practical given the amounts of data needed and costs involved.

2) Creation of simulation models

This technique analyzes driving data and creates simulation models to enable calculation of running distance. They include resistance models that consider rolling resistance at different locations on a road as well as vehicle speed, headwinds, etc. and relational models that link weight, running distance, and power consumption. This technique is practical as long as the

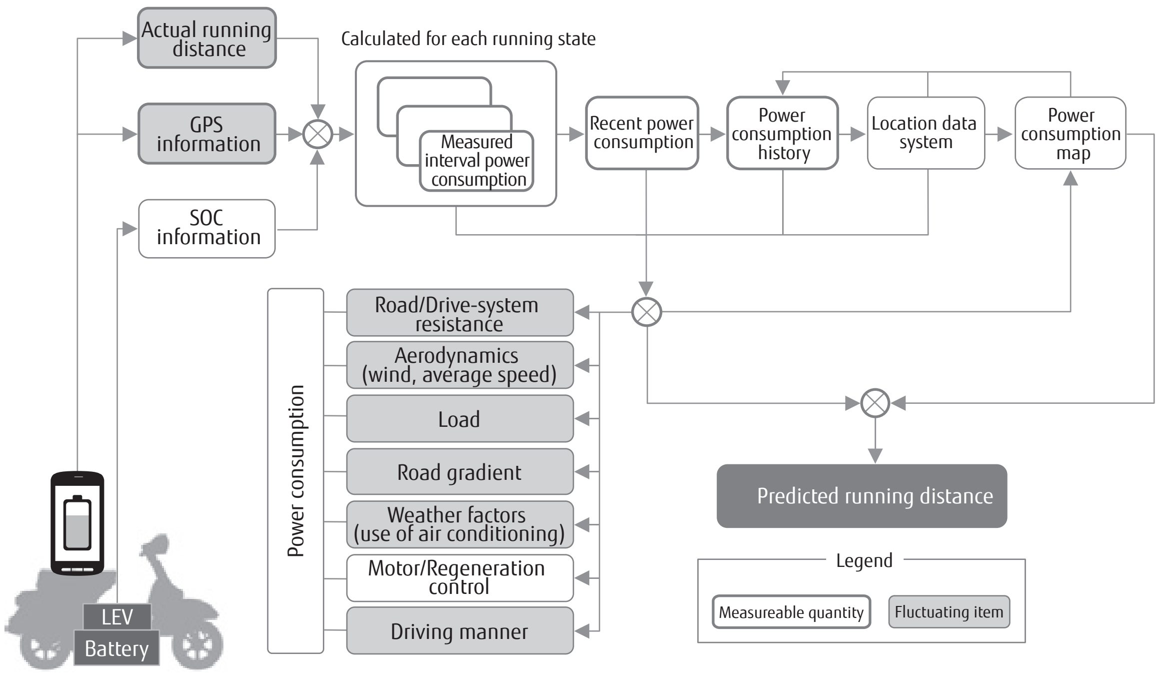

Figure 5
Flow of running distance calculation.

underlying conditions remain simple, but for locations or situations in which conditions become complicated and intertwined, the above types of models cannot be adequately separated. Additionally, if the parameters determining such conditions cannot be input when using the models, calculations will not be possible. On the other hand, driving experiments in which some parameters can be reliably set can be used to produce average models or to show how those parameters affect running distance. This can be a useful method of analysis for obtaining a deeper understanding of target phenomena.

3) Adaptive correction of a power consumption map

This technique continuously obtains data while the vehicle is running, calculates an interval-based power consumption model for the current location on that day from recent data, i.e., data several minutes or several tens of minutes old, and, using that model, performs corrective predictions on what distance or location can be reached several minutes or several tens of minutes into the future. In this way, running distance can be predicted even without map data into the near future, which corresponds to a time period in which the probability of conditions changing is low. Nevertheless, to improve reliability and accuracy, we can create a power consumption map linked to map data to record power consumption values along the routes traveled. Then, by looking for road-interval data, preferably from recent interval data corresponding to the same gradient as that of roads to be traveled, we can calculate and predict power consumption for each such interval. Running distance can then be calculated by integrating the results for power consumption obtained in this way for the actual road to be traveled. In addition, comparing the running distances so obtained with average values for the same model of vehicle and with one's own vehicle history can uncover practical and useful information.

In performing detailed calculations, model calculation processing that takes the current driving state into account may be performed in proximity to the battery while analysis-system calculations such as checking against power consumption history or updating the power consumption map can be performed by intermittently connecting to the cloud (Figure 5).

Technique 3) above is more practical than techniques 1) and 2). It requires minimal preparation and can be used even if an extensive data set and models have yet to be prepared. This is because predictions for a point in time about five minutes into the near future can be made from data obtained from measurements performed five minutes earlier during a trip. If such data from actual measurements are stored, calculation efficiency is raised and reliability and accuracy are improved. It is sufficient to use only typical values obtained from statistical processing as information to be accumulated and saved. In addition, organizing and storing universal potential energy values and the amount of work needed for movement per interval (= accumulated loss less potential energy difference), for example, will also facilitate calculations while expanding the applicability of this technique since such values can be used by other vehicles and batteries. This technique is also flexible since predictions can be calculated using general values without modification in cases where the effects of various parameters cannot be fully understood.

Given a situation in which the vehicle's load, for example, differs from past loads, the average work needed for moving the vehicle in the last 1–5 minutes or the work needed to move the vehicle along a short interval in the road can be compared with statistical values such as movement-related work obtained from the vehicle's history. In this way, a general coefficient can be obtained that indicates the extent to which interval values on the route being traveled should be corrected. For example, if even a somewhat general value expressed in the form of "1.4 times worse than usual" can be obtained, past values plotted on a map can be multiplied by 1.4 and running distance predicted. Even if all relevant parameters or conditions cannot be rigorously determined, the capability of outputting predictions at least for the near future is still useful and practical.

In addition to the effects of uphill roads and rain and wind, technique 3) can incorporate changes in the amount of luggage, number of passengers, etc. during a trip, thereby enabling more accurate predictions to be made.

Furthermore, establishing a continuous cloud connection with a location data platform makes it possible to store and classify pieces of data such as how the battery is used or how it changes at what locations and under what situations. In short, a cloud connection would greatly increase the possibility of obtaining useful feedback for developing a better understanding of cause-and-effect relationships in battery operation and improving the performance of both batteries and EVs.

5. Future developments

Economic benefits and low barriers to implementation are important factors in the spread of a "cloud-connected battery management system" that connects shared batteries to the cloud. Such a system has several advantages and possibilities.

1) The system can quickly and flexibly supply electrical energy to places like outlying regions or sightseeing areas with no transmission lines, where power and EV demand can fluctuate, and to areas affected by a natural disaster. At the same time, it can reduce CO_2 emissions and facilitate energy management by quantifying that reduction, thereby making it a good match for the needs of the times for both developing and developed countries.
2) The system can determine the status of dispersed batteries on an individual basis, including the way in which each battery is being used and the state of degradation of each battery. This means that information indicating the value of a battery can be clearly presented at all times, which opens up a variety of possibilities, as touched upon below.

- In contrast to having individuals purchase expensive batteries on their own and keep them at their homes, a business model can be envisioned that enables batteries to be shared by many users and stored in a dispersed manner and that has users pay only for what they use or consume. This model will enable individual EV users to use their EVs anywhere in a much more convenient manner while enjoying a low cost of introduction to EV use. It will also enable sharing-service providers to obtain a quantitative understanding of their good customers and reward them appropriately for their patronage.
- The overall value of shared battery assets can be determined and optimized, depreciation can be systematically managed, and anti-crime measures can be enhanced.
- The replacement time of batteries can be thoroughly managed since each battery's state of degradation is known, and the total cost of battery assets can therefore be optimized. For example, any one battery can be exchanged when its remaining capacity has reached a predetermined value such as 80%. In the past, batteries were replaced on the basis of total usage time or total number of charges with no regard to individual variation, which meant that even batteries with no degradation could be thrown out and value lost. A cloud-connected battery management system can reduce this type of economic loss to nearly zero. This effect is greater the more expensive the batteries.
- Visualizing the way in which each battery is used and the extent of its degradation makes it possible to determine the actual value of each battery. As a result, a battery can be assigned a sales price appropriate to its remaining lifetime when it is sent to a secondary battery market such as for stationary applications. In this way, the nature of the business model and the sense of product value can be expected to change.

6. Conclusion

Electric vehicles, deemed essential to reducing CO_2 emissions, are on the path toward expanded use. Two keys to this expansion are a battery replacement system and a location data cloud. A "cloud-connected battery management system" that links this replacement system and data cloud and manages individual replacement batteries enables an e-mobility society and new business models that will revolutionize the usage scenarios and values of EVs and batteries. In addition, technologies for determining where and by how much energy is being used and CO_2 emissions are being reduced can be envisioned through cloud-connected batteries.

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