

# Modeling of Efficient Lifetime Prediction for Lithium-ion Battery Employing Orthogonal Array

Kaoru OMICHI<sup>1</sup>Tadashi KAGA<sup>1</sup>Takumi NISHIMURA<sup>1</sup>Naoya AIDA<sup>1</sup>Yuki TOMINAGA<sup>1</sup>

## ABSTRACT

Estimation of lithium-ion battery durability by modeling that simulates performance degradation is an important technology during the initial phase of development of electrified products. For this study, a low-cost, highly efficient technique for creating a model was investigated by applying the orthogonal array used in quality engineering to the process of creating a performance degradation prediction model. As a result, it was found that for the storage durability test, it was productive to apply an experimental design that uses an L16 orthogonal array, whereas for the cycle durability test, it was productive to apply an experimental design that uses an L27 orthogonal array. It was also found that by fitting to the test results, when the storage degradation coefficient is modeled by expressing it with the state of charge and temperature in a quadratic linear equation together with an interaction term, and the cycle degradation coefficient is modeled by expressing it with the state of charge, window of operating state of charge, temperature, charge current, and discharge current in a first-order linear equation, then it was possible to simulate the results of accelerated durability testing highly accurately with a deviation of 1.3%. The method of modeling discussed in this paper reduced the amount of testing necessary in the conventional, factorial experiment method by 58% while realizing an equivalent level of accuracy, confirming that enhancement of experiment efficiency can be expected.

## 1. Introduction

Since lithium-ion batteries (LiBs) have high energy density and power density, they are coming into wide use not only in compact electronic equipment, but also in the large-scale mobility of motorcycles, automobiles, and aircraft<sup>(1)-(4)</sup>. Durability in LiBs for electric vehicles such as hybrid electric vehicles (HEVs), battery electric vehicles (BEVs), and so on, has been sought over a period of 10 years or more, and various regions and patterns of use also have to be taken into consideration. It is necessary, therefore, to confirm by means of prediction using a model simulating performance degradation (hereinafter, degradation prediction model) whether the durability satisfies development objectives in the initial phase of development<sup>(5), (6)</sup>. The rate of LiB degradation depends on the temperature and state of charge (SOC) of a battery in storage, the current while charging, the current while discharging, the magnitude of changes in the SOC, and other such factors. Consequently, the rate of degradation of a battery changes according to the environment where the electric vehicle is used and how it is used. In general, when a user drives frequently in a region with high temperatures

and repeatedly accelerates and brakes suddenly, then the battery in that user's electric vehicle will undergo degradation sooner than one in the vehicle of a user in a region with low temperatures who does not drive frequently and who accelerates and brakes gently. A degradation prediction model needs to have functions that work out the rate of degradation to match the various ways in which such electric vehicles are used and calculate cumulatively the amount of degradation per unit of time<sup>(7)</sup>. At Honda up to now, a semi-physical model has been created that very accurately calculates performance degradation behavior by predicting the internal state of a battery<sup>(8), (9)</sup>. Going forward, there will be a need for efficient creation of highly accurate prediction models to meet the further increasing need for electric vehicle development. In order to efficiently create prediction models, it is necessary to set conditions for testing whether they satisfy development objects and to investigate optimal methods for creating models.

Figure 1 shows a simplified view of the flow of the simulation of degradation behavior in the repetition of park-drive-charge modes implemented by Honda. The LiB performance is expressed by its capacity retention, which diminishes as the battery is used. The rates of degradation

<sup>1</sup> Innovative Research Excellence Power Unit & Energy

E-mail: Kaoru\_Omichi@jp.honda

corresponding to the individual park-drive-charge modes of use are calculated from a degradation coefficient map that is created in advance by fitting with the training data from durability tests. The calculated rate of degradation and the time period during the mode ( $\Delta time$ ) are multiplied together to calculate the amount of degradation during each mode. These are added together to predict the amount of degradation. In order to predict degradation with high accuracy, it is necessary to account for a large number of conditions in a way that will include usage by users and to conduct long-term tests. However, durability tests of on-board batteries involve a charge-discharge machine for charging and discharging the batteries, a thermostatic chamber, an evaluation device for reading electrical properties, the expense of personnel to conduct the durability tests, and so on. As these are needed for extended periods of time, there is a large cost burden. In this study, therefore, an experimental design based on orthogonal arrays was applied in creating an LiB model, the number of tests was reduced, and a highly accurate method of modeling was realized.

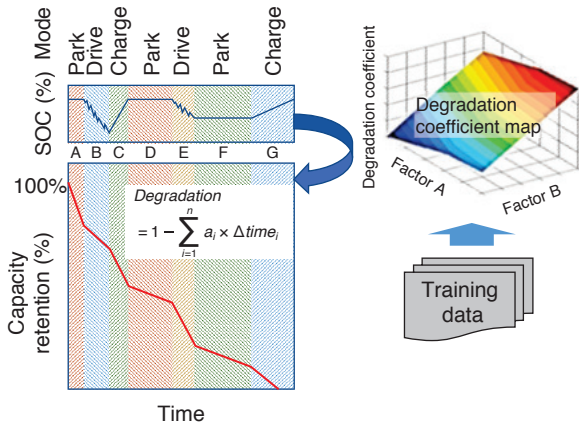


Fig. 1 Concept of calculating performance degradation

## 2. Current Issues and Proposals

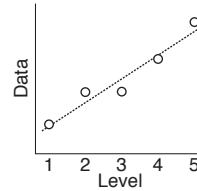
Up to now, Honda has been conducting durability tests with 100 or more load conditions over a period of half a year or more in order to create degradation prediction models for on-board LiBs. The tests have been conducted with a focus on battery load using two types of tests: storage mode (parked) and cycle mode (driving and charging). The test conditions have been set according to fractional factorial experiment to five levels or more for each degradation factor. Figure 2 shows an example. For each factor (from A to E), five levels are set. In this method, factors other than the focal factors are fixed (the gray cells in Fig. 2(b)), and only the focal factors are changed one level at a time, thereby obtaining test data on factorial effect

that can be analyzed. The advantage is that the effect due to the change of a single factor can be obtained directly so that the readability of the data is high and the data can readily be understood intuitively. For example, plotting the test data items 1 to 5 from Fig. 2(b) in the factorial effect diagram in Fig. 2(c) makes it possible to readily grasp that there is a steady upward trend. The disadvantage, on the other hand, is that the various test levels are concentrated on a certain level, and as a result there is a concern that imbalance between levels may occur when viewing the data as a whole. The imbalance of levels tends to diminish the robustness of the prediction model. In addition, when deriving the factorial effect, one data item is extracted per level in order to grasp the dependency of each factor, and thus there is a susceptibility to being affected by variation and noise. In order to address this issue, the fixed levels were changed and two to three sets of fractional factorial experiments were conducted. This resulted in the issue, however, that the number of durability test conditions became large, ranging from 65 to 100 conditions, and the testing cost became high.

In this study, these issues were addressed by applying an orthogonal design. Figure 3 shows basic experimental designs created with two levels of each factor. Three

|        |   | Level |    |    |    |    |
|--------|---|-------|----|----|----|----|
|        |   | 1     | 2  | 3  | 4  | 5  |
| Factor | A | A1    | A2 | A3 | A4 | A5 |
|        | B | B1    | B2 | B3 | B4 | B5 |
|        | C | C1    | C2 | C3 | C4 | C5 |
|        | D | D1    | D2 | D3 | D4 | D5 |
|        | E | E1    | E2 | E3 | E4 | E5 |

(a) Level / Factor matrix



(c) Factorial plot

| Experiment No. | Factor |    |    |    |    |
|----------------|--------|----|----|----|----|
|                | A      | B  | C  | D  | E  |
| 1              | A1     | B1 | C1 | D1 | E1 |
| 2              | A2     | B1 | C1 | D1 | E1 |
| 3              | A3     | B1 | C1 | D1 | E1 |
| 4              | A4     | B1 | C1 | D1 | E1 |
| 5              | A5     | B1 | C1 | D1 | E1 |
| 6              | A1     | B2 | C1 | D1 | E1 |
| 7              | A1     | B3 | C1 | D1 | E1 |
| 8              | A1     | B4 | C1 | D1 | E1 |
| 9              | A1     | B5 | C1 | D1 | E1 |
| *              | A3     | B3 | C3 | D3 | E3 |
| *              | A3     | B3 | C3 | D3 | E4 |
| *              | A3     | B3 | C3 | D3 | E5 |

Note: Grey cell is unchanged from cell above it

(b) Test design

Fig. 2 Conventional testing method

| Experiment No. | Factor |   |   |   |   |
|----------------|--------|---|---|---|---|
|                | A      | B | C | D | E |
| 1              | 1      | 1 | 1 | 1 | 1 |
| 2              | 2      | 1 | 1 | 1 | 1 |
| 3              | 1      | 2 | 1 | 1 | 1 |
| 4              | 2      | 2 | 1 | 1 | 1 |
| 5              | 1      | 1 | 2 | 1 | 1 |
| 6              | 2      | 1 | 2 | 1 | 1 |
| 29             | 1      | 1 | 2 | 2 | 2 |
| 30             | 2      | 1 | 2 | 2 | 2 |
| 31             | 1      | 2 | 2 | 2 | 2 |
| 32             | 2      | 2 | 2 | 2 | 2 |

Note: Colored cells show level 2

(a) Full factorial experiment

| Experiment No. | Factor |   |   |   |   |
|----------------|--------|---|---|---|---|
|                | A      | B | C | D | E |
| 1              | 1      | 1 | 1 | 1 | 1 |
| 2              | 2      | 1 | 1 | 1 | 1 |
| 3              | 1      | 2 | 1 | 1 | 1 |
| 4              | 1      | 1 | 2 | 1 | 1 |
| 5              | 1      | 1 | 1 | 2 | 1 |
| 6              | 1      | 1 | 1 | 1 | 2 |

(b) Fractional factorial experiment

| Experiment No. | Factor |   |   |   |   |
|----------------|--------|---|---|---|---|
|                | A      | B | C | D | E |
| 1              | 1      | 1 | 1 | 1 | 1 |
| 2              | 1      | 1 | 1 | 2 | 2 |
| 3              | 1      | 2 | 2 | 1 | 1 |
| 4              | 1      | 2 | 2 | 2 | 2 |
| 5              | 2      | 1 | 2 | 1 | 2 |
| 6              | 2      | 1 | 2 | 2 | 1 |
| 7              | 2      | 2 | 1 | 1 | 2 |
| 8              | 2      | 2 | 1 | 2 | 1 |

(c) Orthogonal array design

Fig. 3 Variations of basic designs of experiments

designs are shown. The full factorial experiment tests the combinations of each factor at all the levels. The fractional factorial experiment tests a portion of the factorial effect. The orthogonal array design tests the factorial effect on the basis of an orthogonal array.

In an orthogonal array design, each level is included in the test conditions the same four times in each factor, and the combinations of factors are orthogonal. Because of this, the factor characteristics of each level can be calculated as the average of the characteristic values of the four tests. The fact that the data can be averaged and handled is a link with factorial effect analysis, which has little variation. It also becomes possible to have combinations that are balanced for each level, which increases the model's robustness. In addition, it is possible to greatly reduce the number of test conditions compared to the full factorial experiment.

### 3. Process Development

In obtaining efficient model training data, it is desirable to acquire highly reliable data without reducing model prediction accuracy. Here, model prediction accuracy means the degree of divergence between training data and other test data used for verification. Highly reliable data means data that is less influenced by noise. In order to obtain data for creating an LiB degradation prediction model using the orthogonal array described above, data acquisition was carried out with attention to the following matters.

#### 3.1. Orthogonal Array Size Optimization

An orthogonal array is denoted by the letter L combined with a number indicating the number of experiments, as in L8 and L16. There are many orders of orthogonal array, such as L8, L9, L16, L18, L25, L27, L32, L36, and so on. When the size of an orthogonal array is decided, then the number of levels and the number of factors that can be evaluated are automatically limited. For example, if an orthogonal array is an L9, then it will be possible to evaluate at most four factors on three levels. When there is visible interaction between factors, then the number of factors that can be evaluated is further reduced. Out of these kinds of constraints, it is necessary to take into consideration the factors that should be evaluated and the number of levels that should be evaluated when selecting an orthogonal array. There are two main types of LiB modes of use: storage mode and cycle mode. The factors that determine the magnitude of their respective loads are, for storage mode, the two factors of temperature and SOC, whereas for cycle mode, the load is determined by the five factors of temperature, SOC,  $\Delta$ SOC, charge current (I-charge), and discharge current (I-discharge) (Fig. 4)<sup>(9)</sup>. In deciding the number of levels, it is necessary to take into consideration the linearity of the characteristic values for each factor. If the factorial effect is linear, then it is possible to approximate a straight line from the test results for two levels. If it is non-linear, however, it will be necessary to set

at least three levels and to model the results by the response surface method. For this study, the optimal orthogonal array was configured from the analysis of on-board LiB durability test results.

#### 3.2. Optimization of the Number of Levels

When setting the levels, it is necessary to take into consideration two things: the feasibility of the test and the level extrapolation risk. In experimental design based on an orthogonal array, the occurrence of incomplete testing and missing data undermines the reliability of the data as a whole. Therefore it is necessary to set test levels that are realizable. As tests that are set with conditions at the usage limit value for multiple factors may sometimes turn out to be not possible to execute, these were avoided. However, when the range of levels set is conspicuously narrower than the usage range, it is necessary to calculate the degradation coefficient from outside the range of levels set by extrapolation, and this can become a cause of increased prediction deviation. Levels were therefore set to the largest possible range while keeping the balance among factors and staying within the range of possible test execution.

#### 3.3. Model Formula Development

For the model formula, it is necessary to select the model formula that is best capable of reflecting the training data and that is capable of making accurate predictions with respect to verification data that is separate from the training data. In the formulas formulated as candidates for the model, the number of terms and the order were controlled and multiple models with differing degrees of complexity were prepared.

#### 3.4. Model Formula Selection

In selecting the model formula, it is necessary to make the determination from the coefficient of determination  $R^2$  for the training data and the simulation deviation with respect to verification data. A model formula that is complex, with an order and coefficients that are large, will fit well with the training data, but a state of overfitting may

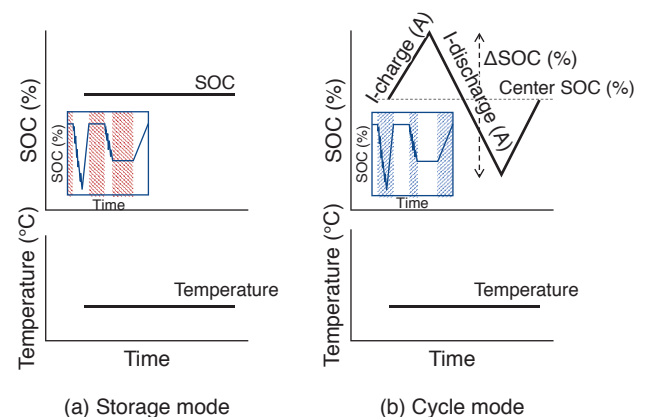


Fig. 4 Factors of storage and cycle modes

sometimes occur when accuracy is reduced with respect to conditions other than the training data, such as verification conditions. For this reason, multiple model formulas were planned based on the LiB degradation characteristics and with differing degrees of complexity. From among those, the model formula with the highest accuracy was selected using the coefficient of determination and simulation deviation as indices.

#### 4. Process Investigation Results

Durability tests were conducted under many conditions and the test results were analyzed in order to investigate methods suited to the creation of LiB degradation prediction models. The tests used LiBs of the 5-Ah class for hybrid use as samples. Durability tests were conducted over a six-month period by factorial experiment with 95 conditions in all for both storage durability tests and cycle durability tests. The rate of degradation under each condition was calculated using a general model formula, Eq. (1)<sup>(10)</sup>, that expresses LiB durability behavior, and the parameters of the model formula were identified by the least squares method.

$$\text{Capacity retention} = a \times \text{Time}^{0.5} + 1 \quad (1)$$

$$\begin{aligned} \text{Degradation coefficient} \\ &= a_{11} \times \text{SOC}^2 + a_1 \times \text{SOC} \\ &+ a_{22} \times \text{Temperature}^2 \\ &+ a_2 \times \text{Temperature} \\ &+ a_{12} \times \text{SOC} \times \text{Temperature} \\ &+ a_0 \end{aligned} \quad (2)$$

##### 4.1. Orthogonal Array Selection

Figure 5(a) and (b) show factorial effect diagrams that have the degradation coefficient  $a$  calculated from the results of each test plotted against each factor. Figure 5(c) shows the response surface obtained on the basis of a quadratic model formula, Eq. (2). The storage durability tests indicated the non-linearity of the SOC dependency and temperature dependency, which meant that it would be necessary to select an orthogonal array allowing selection of three levels or more. Also, the fact that the slope of the SOC dependency changed according to the temperature suggested that there was an interaction between the SOC and the temperature. These results pointed to an orthogonal array having three levels or more for two factors and allowing evaluation of interaction, and as such it was found to be desirable to use a three-level L9 orthogonal array and an L16 that transforms a two-level orthogonal array into four levels.

Figure 6 shows the factorial effect analysis results from the cycle durability tests. The dependencies show a steady upward trend with respect to five factors, and non-linear behavior was observed in three of those five factors,

namely temperature,  $\Delta\text{SOC}$ , and I-charge. Also, with regard to the four factorial effects other than SOC, slopes that differed according to the SOC were observed when factorial effects under differing SOC were evaluated. This can be considered to occur because there are interactions in

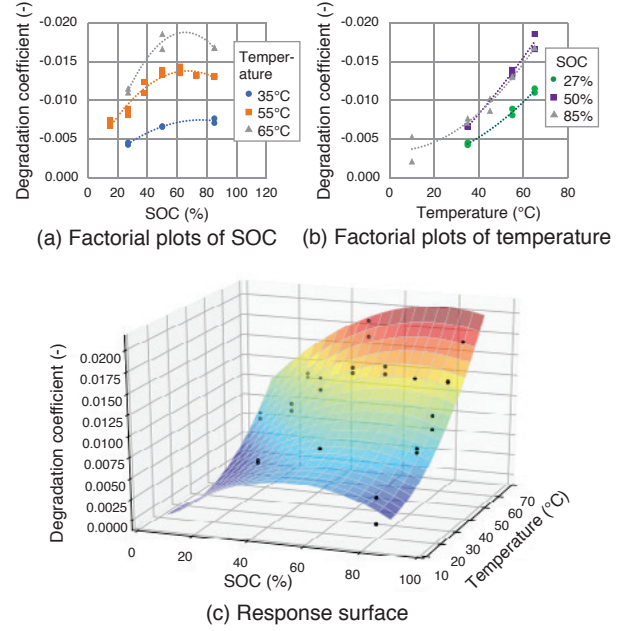
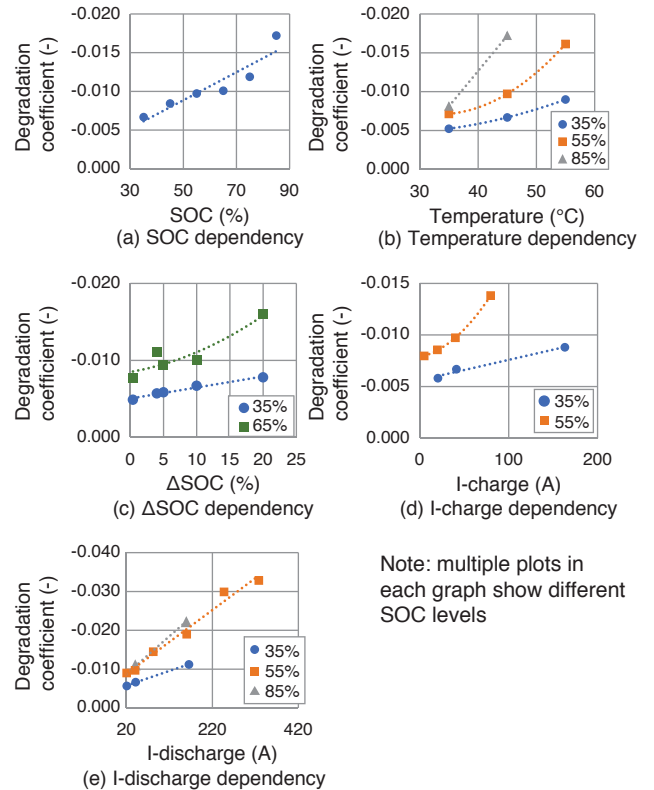


Fig. 5 Factorial plots and response surface of two variables in storage mode



Note: multiple plots in each graph show different SOC levels

Fig. 6 Factorial plots of five factors in cycle patterns

each factorial effect. It was found from these results that an L27 that enables factor analysis of three levels or more and that enables evaluation of four types of interaction at most would be appropriate for the cycle durability test. The total number of tests necessary for the storage durability test (L16) and the cycle durability test (L27) comes out to the sum of 16 and 27, or 43 conditions.

#### 4.2. Selection of Levels

When setting the levels for each factor, it is necessary to consider factors that are completely independent and factors that are not independent separately. Factors of SOC and temperature in the storage durability test are independent. In the cycle durability test, on the other hand, I-charge and I-discharge, and center SOC and  $\Delta$ SOC, are not independent because the sums of the values of each pair are constrained. Figure 7 shows those constraints. The range of values that can be taken by I-discharge and I-charge is at or below the upper limit on current value in the battery specifications, and it is necessary to conduct tests at or below the effective current value (A-rms limit) at which cell heat generation does not become an issue [Fig. 7(a)]. When the amount of heat generated in the cell is large, battery temperature cannot be readily controlled. In order to conduct tests safely, levels were also set so that the range of the sum of the center SOC and  $\Delta$ SOC would be such that it did not cause the over-discharge phenomenon and lithium plating phenomenon even when overvoltage is taken into account [Fig. 7(b)]. For conditions that have factor values outside the level setting range, it becomes necessary to determine the degradation coefficient by extrapolation, and thus levels were selected so that the highest level values could be chosen with all the variables kept in balance.

#### 4.3. Planning the Model Formula

Multiple model formulas were created while adjusting their complexity by the order of the factorial effect and the number of terms in the model formula. With regard to the order, first-order linear and quadratic linear versions were prepared. With regard to the number of terms, interaction terms were added and reduction of the number of terms was carried out by analysis of variance. Six types of model formula were planned, as shown in Table 1. With regard to

Table 1 List of model formulas

| No.   | Model                           | Formula                                                                                                              | Number of coefficients |
|-------|---------------------------------|----------------------------------------------------------------------------------------------------------------------|------------------------|
| (i)   | Linear                          | $\sum_{i=1}^5 a_i \times X_i + a_0$                                                                                  | 6                      |
| (ii)  | Linear + interaction            | $\sum_{i=1}^5 a_i \times X_i + \sum_{i=2}^5 a_{1,i} \times X_1 \times X_i + a_0$                                     | 10                     |
| (iii) | Quadratic                       | $\sum_{i=1}^5 a_{i,i} \times X_i^2 + \sum_{i=1}^5 a_i \times X_i + a_0$                                              | 11                     |
| (iv)  | Quadratic + interaction         | $\sum_{i=2}^5 a_{i,i} \times X_i^2 + \sum_{i=1}^5 a_i \times X_i + \sum_{i=2}^5 a_{1,i} \times X_1 \times X_i + a_0$ | 21                     |
| (v)   | Linear + interaction (ANOVA)    | $\sum_{i=1}^5 a_i \times X_i + a_{1,3} \times X_1 \times X_3 + a_0$                                                  | 7                      |
| (vi)  | Quadratic + interaction (ANOVA) | $\sum_{i=2}^5 a_{i,i} \times X_i^2 + \sum_{i=1}^5 a_i \times X_i + a_{1,3} \times X_1 \times X_3 + a_0$              | 12                     |

$X_1$ : SOC;  $X_2$ : Temperature;  $X_3$ :  $\Delta$ SOC;  $X_4$ : I-charge;  $X_5$ : I-discharge

Table 2 Analysis of variance of L27 cycle mode test

| Factor                    | Degree of freedom | Sum of squares | Mean square | F-value | p-value | Statistical significance |
|---------------------------|-------------------|----------------|-------------|---------|---------|--------------------------|
| Center SOC                | 2                 | 7.5E-05        | 3.7E-05     | 4.7E+01 | 0.002   | *                        |
| Temperature               | 2                 | 1.2E-04        | 5.8E-05     | 7.3E+01 | 0.001   | *                        |
| $\Delta$ SOC              | 2                 | 2.1E-04        | 1.1E-04     | 1.3E+02 | 0.000   | *                        |
| I-charge                  | 2                 | 1.1E-05        | 5.5E-06     | 7.0E+00 | 0.049   | *                        |
| I-discharge               | 2                 | 5.0E-05        | 2.5E-05     | 3.2E+01 | 0.004   | *                        |
| Center SOC x I-charge     | 4                 | 1.0E-06        | 2.5E-07     | 3.2E-01 | 0.853   |                          |
| Center SOC x $\Delta$ SOC | 4                 | 1.8E-05        | 4.5E-06     | 5.6E+00 | 0.061   | *                        |
| Center SOC x Temperature  | 4                 | 2.8E-06        | 7.0E-07     | 8.9E-01 | 0.544   |                          |
| Errors                    | 4                 | 3.2E-06        | 7.9E-07     | -       | -       |                          |
| Total                     | 26                | 4.9E-04        | 2.2E-05     | -       | -       |                          |

\*Lower than the alpha level of 0.10

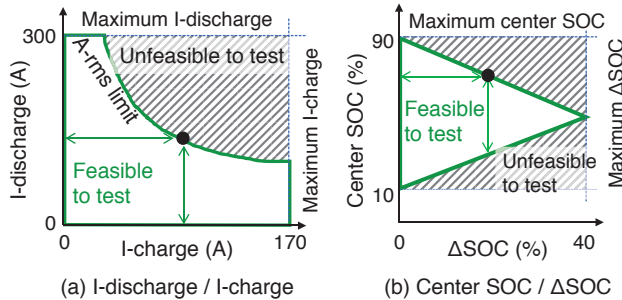


Fig. 7 Trade-off factors in cycle mode

the degradation factor, linear Models (i)(ii)(v) with factorial effects that are in first-order linear form were formulated. Those to which simple linear form did not apply were formulated as quadratic linear Models (iii)(iv)(vi), and analysis-of-variance (ANOVA) Models (v)(vi) made up only of statistically significant terms were formulated. In order to select the statistically significant terms, the results of tests conducted using the orthogonal array were analyzed by analysis of variance, as shown in Table 2, and the statistically significant terms (those factors in Table 2 marked with asterisks) were identified by the F-test. The F-test is a method for determining whether or not there is a significant difference in the variance between two factors, that is, the variation. In the analysis of variance, significant factors can be identified by conducting F-tests of the variance from each factorial effect and of the variance from the deviation factors. Since factors determined not to be significant disrupt the accuracy of the model, they are excluded as much as possible. In this study, six factors out of the five principal factors and four interactions were determined to be statistically significant.

Table 3 Simulation results of six models

|       | Model                           | Number of coefficients | Coefficient of determination ( $R^2$ ) vs training data | RMSE (%) vs test data |                 |         |
|-------|---------------------------------|------------------------|---------------------------------------------------------|-----------------------|-----------------|---------|
|       |                                 |                        |                                                         | Simple pattern        | Driving pattern | Average |
| (i)   | Linear                          | 6                      | 0.92                                                    | 2.2%                  | 1.1%            | 1.6%    |
| (ii)  | Linear + interaction            | 10                     | 0.95                                                    | 6.4%                  | 1.0%            | 3.7%    |
| (iii) | Quadratic                       | 11                     | 0.93                                                    | 3.3%                  | 2.1%            | 2.7%    |
| (iv)  | Quadratic + interaction         | 15                     | 0.97                                                    | 6.7%                  | 2.8%            | 4.7%    |
| (v)   | Linear + interaction (ANOVA)    | 7                      | 0.94                                                    | 3.0%                  | 1.6%            | 2.3%    |
| (vi)  | Quadratic + interaction (ANOVA) | 12                     | 0.98                                                    | 7.4%                  | 1.4%            | 4.4%    |

#### 4.4. Model Formula Selection

The model formulas were selected from among the six types of model formula in Table 1 by means of the coefficient of determination  $R^2$  of the training data and the simulation deviation (root mean square error: RMSE) from the verification data. Verification test results different from the training data were prepared for use in selecting the model formulas, and those formulas with higher prediction accuracy were selected. It is necessary to prepare multiple test data as much as possible and to select the model formulas comprehensively. In this study, simple patterns that combine multiple training test conditions and complex actual driving patterns were set as test conditions, and the data from durability tests conducted over the same period (four months) as the training tests were used as data for verification. The coefficient of determination of the training data for each model and the deviation from the test data used for verification are shown in Table 3. Of these, Model (i) was successfully fitted to the training data with a coefficient of determination of 0.9 or higher, and its prediction has the lowest deviation from the test data used for verification. Therefore it was determined that the linear model of Model (i) was good. The reason that the linear Model (i) had the best accuracy this time is thought to be that it was a simple model formula that had fewer coefficients than the other Models (ii) through (vi) and thus was more robust in its predictions of patterns that differed from the training data. As data that supports this reasoning, the results from the analysis of variance (Table 2) described above show that the terms included in the linear models (SOC, temperature,  $\Delta$ SOC, I-charge, I-discharge) have low p-values in all eight terms. Here the p-value indicates the probability from 0 to 1 that there will be significance in the variance values based on the variance ratio of each factor and the deviation factors and the degree of freedom. The closer the value is to 0, the greater the variance by comparison to the deviation factors, which means it is significant. The Model (i) formula is considered to have enhanced prediction accuracy because the formula is made up of statistically significant terms.

## 5. Degradation Prediction Results

Cycle mode data was obtained using the L27 orthogonal array with 27 tests, and Fig. 8 shows the results from prediction of accelerated durability testing at the high temperature of 45°C using the optimized model. The accelerated durability testing simulated the waveform applied to the battery cells during actual driving. The result was an RMSE of 1.3% for the deviation between the prediction results and the measured values.

Meanwhile, durability tests were also conducted not using the orthogonal array but rather the conventional method of fractional factorial experiment that was conducted with 65 conditions. The model was created with the number of conditions used for modeling changed from 18 conditions to 65 conditions, and Fig. 9 shows the accuracy achieved in prediction of accelerated durability testing as plotted against the number of conditions. It is apparent that in the factorial experiment, the deviation decreased as the number of conditions used in modeling increased, indicating that prediction accuracy has been enhanced. The prediction deviation when 65 conditions were used was 1.4%, whereas the prediction deviation with the model created using the orthogonal array with

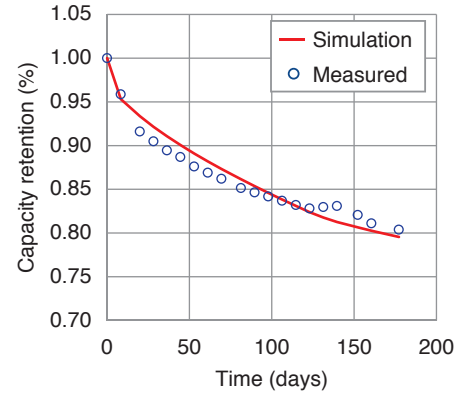


Fig. 8 Simulation result of driving pattern

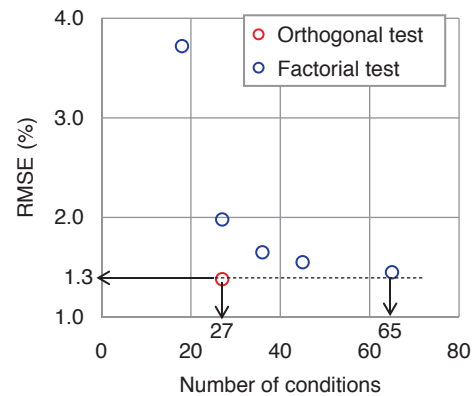


Fig. 9 RMSE of various number of conditions

27 tests was 1.3%. Therefore this confirmed that both approaches yield largely the same values. The model using the orthogonal design had prediction accuracy equivalent to the conventional method while reducing the number of conditions by 58%.

## 6. Conclusion

In creating an LiB performance degradation prediction model, the process of acquiring training data based on an orthogonal array and the method of modeling were investigated. The results yielded the findings below.

- (1) The orthogonal arrays suited to acquiring the training data necessary in creating an LiB degradation model are L16 (storage durability test) and L27 (cycle durability test).
- (2) For the battery degradation model formulas used in this study, the quadratic linear model with interaction is optimal for storage degradation and the first-order linear model is optimal for cycle degradation.
- (3) Implementing test design using the orthogonal array yielded prediction results that maintained the same 1.3% accuracy while reducing the number of conditions by 58%.

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### ■ Author ■



Kaoru OMICHI



Tadashi KAGA



Takumi NISHIMURA



Naoya AIDA



Yuki TOMINAGA