

The background of the cover is a complex, abstract geometric structure. It consists of a large, undulating mass composed of a dense mesh of small triangles. The triangles are colored in a variety of hues, including shades of purple, blue, green, orange, and red, creating a vibrant, multi-colored effect. From the base of this main structure, several smaller, similar geometric spheres or clusters of triangles are scattered across the lower portion of the image. The overall style is highly detailed and mathematical, reminiscent of modern digital art or data visualization.

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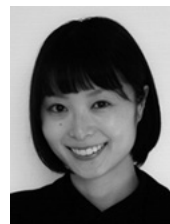
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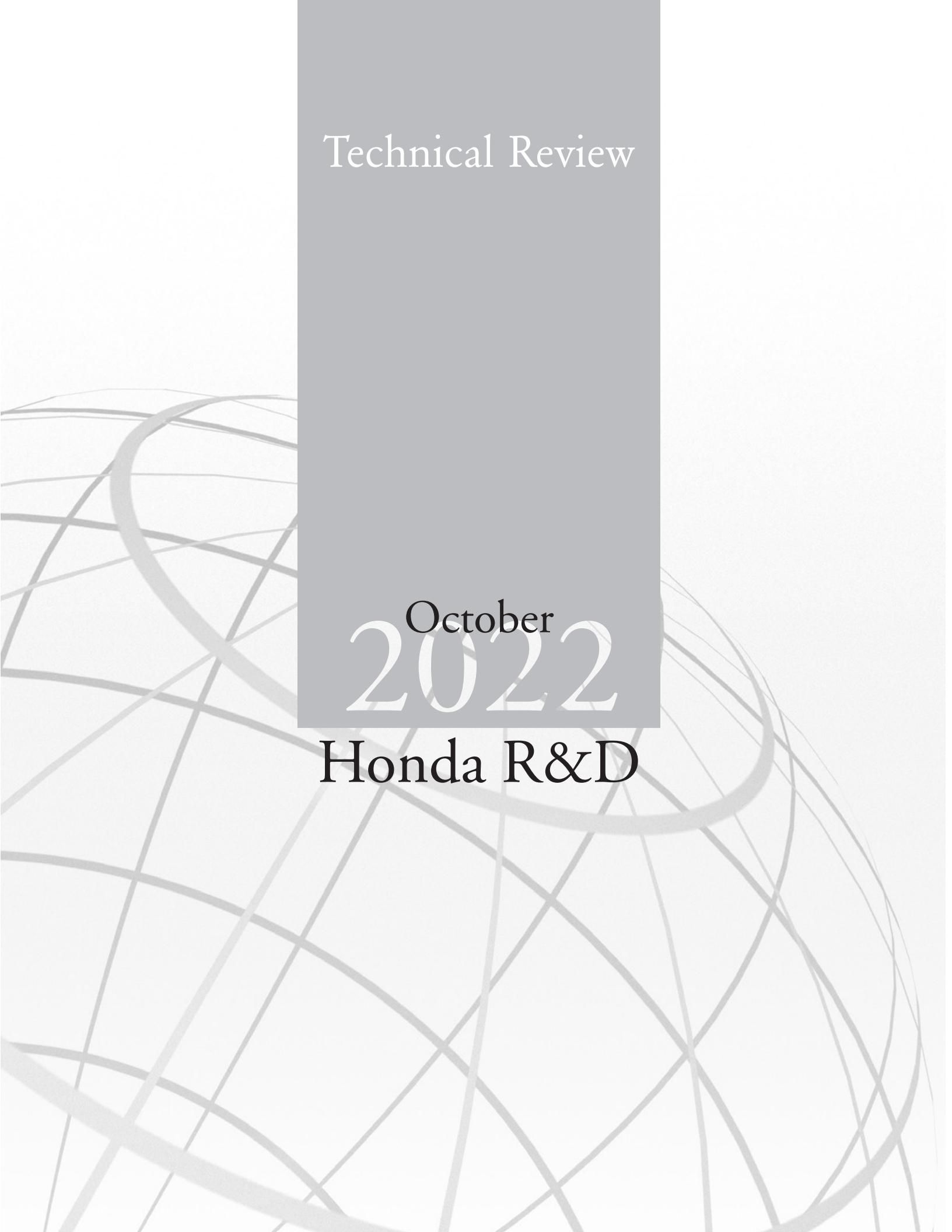


Comment on the Cover

This expresses in a concrete image the way in which a variety of ideas merge to form a single technology. What I sense is that the repeated merging of ideas, and sometimes their fragmentation, ultimately brings form to technology. If that manner of formation is to be made visible and represented, then I would conceive of it as something like a wriggling organic body, and I have expressed that object with a diversity of colors and shapes.



Design Center
Minami SAITO

The background features a light grey wireframe sphere on the left side, composed of intersecting curved lines. A solid grey vertical bar runs down the center of the page, serving as a backdrop for the text.

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Study of Technology for Outdoor Stable Culture of Microalgae for Recycling of CO₂ in Atmosphere

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ABSTRACT

The optimization of culture tank structure and culturing conditions was investigated using Honda's own strain of microalgae and a flat panel photobioreactor for the purpose of creating carbon dioxide fixation technology using microalgae capable of repurposing carbon dioxide in the atmosphere as a valuable resource. The aim is to build a carbon-neutral society. The culturing conditions were configured in terms of the concentrations of the nutrient salt components of nitrogen, potassium, and phosphorus. By adopting a flow guide shape that discharges liquid and gas in a single direction, a flow-field velocity of 0.02 m/sec or higher was achieved for the culture solution. This optimization of the culturing conditions successfully increased microalgae production volume. Regarding the culture tank structure, the heat insulating layer structure made it possible to maintain temperatures within the control range throughout the year. The culture tank was also installed at a 45° tilt, which successfully increased the amount of incident light in the culture tank. Outdoor culture tests incorporating these factors yielded an expectation of algae production volume of 13.5 g/m²/day. These results indicate the possibility that DREAMO will be able to achieve ethanol production volume per planted area that is equal to or better than bioethanol from sugarcane, which is a carbon-neutral fuel.

1. Introduction

In the context of environmental issues and movements to build a carbon-neutral society, attention is being paid in recent years to carbon capture and utilization (CCU) technology, which collects carbon dioxide (CO₂) that has been discharged into the atmosphere and repurposes it as a valuable resource. Various methods for capturing CO₂ are being investigated, including direct air capture (DAC), which collects CO₂ directly from the atmosphere, technology targeting the capture of highly concentrated CO₂ from thermal power stations and other such sources, chemical absorption methods, physical adsorption methods, and so on. The captured CO₂ is used directly in dry ice, welding, and so on, and used as an ingredient in plastics and other chemical products, fuel, concrete, and other such products⁽¹⁾. CCU technology that makes use of microalgae absorbs CO₂ through photosynthetic reaction and converts CO₂ to a valuable substance through biological functions, and thus it is expected to provide conversion to valuable substances at low energy expenditure.

Compared with other biomasses, microalgae yielded greater annual CO₂ fixation volume per planted area than terrestrial plants. The light energy utilization efficiency

of common terrestrial plants 4.6%⁽²⁾ while microalgae are highly efficient with a top theoretical efficiency of 12.0%⁽²⁾ and they have better CO₂ absorption performance. As stated above, microalgae are capable of intracellular conversion of absorbed CO₂ into a variety of valuable substances. It is converted into the raw material of carbohydrates and other such valuable substances inside the microalgae and stored there. It is then possible to repurpose that raw material to make jet fuel⁽³⁾, bioethanol⁽³⁾, feedstock for plastics⁽⁴⁾, among other such uses in industry as well as in the food and medical fields.

Typical microalgae culturing methods that are commonly found are open pond systems, raceway systems, flat panel systems, and so on. The culture tank structure and research conducted for each system have been reported⁽⁵⁾. For the present research, a flat panel system was adopted in order to raise algae production volume per installed area. Figure 1 shows a conceptual image of the culturing equipment.

This paper introduces measures taken with respect to culturing conditions and culturing equipment for the creation of outdoor stable culture technology using a flat panel photobioreactor with the proprietary microalgae strain developed at Honda and multiple culture tanks in a row.

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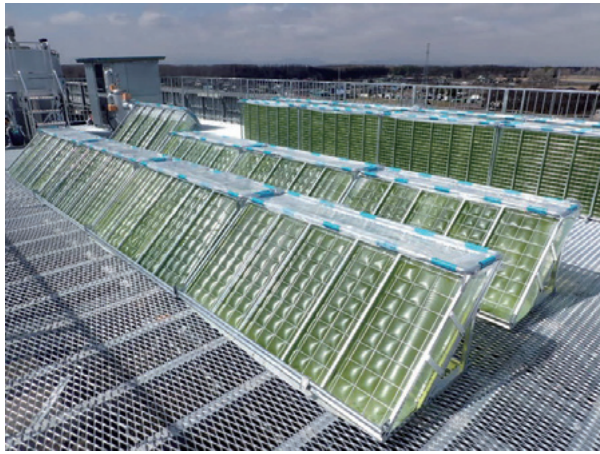


Fig. 1 Image of culture tank equipment

2. Distinctive Characteristics of Honda DREAMO and Outdoor Culture Technology

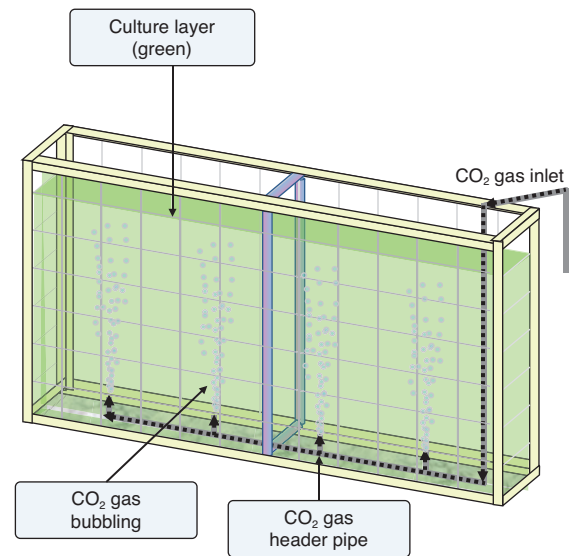
2.1. Distinctive Characteristics of Honda DREAMO Strain

The distinctive characteristics of the microalgae used for this research will be described. Honda's own strain (Honda DREAMO, hereinafter DREAMO) has the *Chlamydomonas reinhardtii* UTEX 90 (National Institute for Environmental Studies: contract NIES-2236) as its parent strain and was acquired by screening without genetic modification. The main distinctive characteristics^{(6), (7)} will be described. The first is that it has a higher production volume per unit area than other microalgae. Different kinds of microalgae have different production volumes, where *Chlamydomonas* of the same species as DREAMO yield from 0.10 to 0.25 g/L/day⁽⁸⁾; and in an ideal indoor environment that is unaffected by the influences of outdoor environmental disturbance, it has the potential to yield the high amount of 0.50 g/L/day. The second is that it is possible to increase its production volume of starch, which becomes the raw material for valuable substances. Generally, the algae production rate and starch content are in a trade-off relationship, but DREAMO can increase the starch content⁽⁶⁾ while maintaining the algae production rate. The third is that while the cell wall of *Chlamydomonas reinhardtii* UTEX 90, which is the parent strain of DREAMO, is 0.3 μm thick, the DREAMO cell wall is thinner, at 0.09 μm . This means that the valuable components stored in the DREAMO cells can be extracted⁽⁷⁾ by a short process.

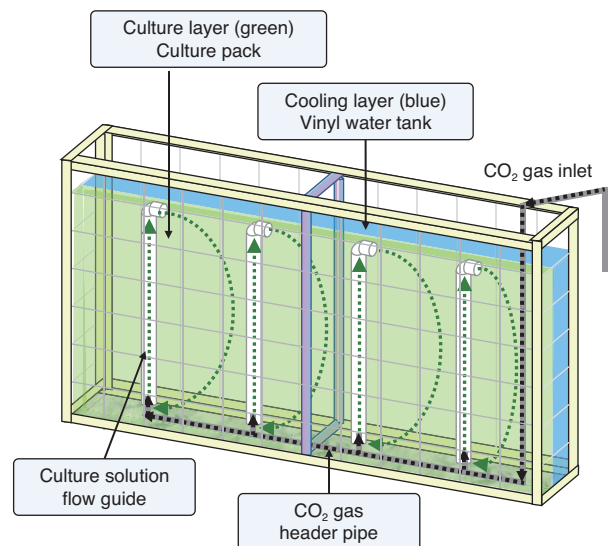
2.2. Flat Panel Photobioreactor

DREAMO culture is carried out in a flat panel photobioreactor in order to raise the algae production volume per installed area. Figures 2(a) and 2(b) show the structures of a general flat panel photobioreactor and of the distinctive Honda flat panel photobioreactor. In the general flat panel photobioreactor in Fig. 2(a), the tank is shallow,

with a depth ranging from 1 to 10 cm⁽⁵⁾, and structured for a water depth of 100 cm⁽⁵⁾ or less. Aeration takes place by discharging CO₂ gas from the piping installed at the bottom of the culture tank, stirring the culture solution. This arrangement suppresses the spontaneous sedimentation of the microalgae. On the other hand, the distinctive characteristics of the Honda original flat panel photobioreactor in Fig. 2(b) are the structure that retains cooling water in the culture tank to use the thermal capacity of the water to hold the temperature control energy for the culture solution down to the lowest possible level, and the structure equipped with flow guides for the culture solution. The culture tank has a



(a) General structure of flat panel type culture tank with culture tank and CO₂ gas bubbling



(b) Honda flat panel type culture tank

Fig. 2 Structural comparison of flat panel type culture tanks (a) and (b)

Table 1 Important factors and issues of DREAMO

Factor	Culture effect	Issue	Theme
Nutrients	Nutrient depletion	Contamination proliferation	Nutrient concentration optimization
Broth stirring	Algae subsidence	CO ₂ dissolution amount, O ₂ dissolved amount, reduced light reception	Stirring speed optimization and structure
Water temperature	Water temperature rise	Increased temperature control energy	Temperature control energy minimization
Incident light	Reduced production efficiency, water temperature rise	Low utilization of incident light, water temperature rise	Incident light utilization rate upward, temperature control energy minimization

vinyl water tank filled with cooling water and a culture pack into which culture solution is injected fixed in place inside the housing. In this structure, the culture pack is placed inside the cooling tank filled with cooling water. In order to reduce the energy used to stir the culture solution, stirring is done by air-lift using supplied gas.

Figure 3 shows the ancillary equipment for the device. This is made up of a feed pump for collecting and injecting the cultured DREAMO, a settlement tank for collecting the culture solution with included DREAMO, and a blower used to supply exhaust gas and other such gas that contains CO₂. The settlement tank is a device with the added function of spontaneous sedimentation of cultured DREAMO in the primary concentration.

2.3. Issues in Outdoor DREAMO Culture

Increasing microalgae production volume involves numerous issues⁽⁹⁾. Table 1 shows those culture factors^{(6), (7), (9)} and those culture effects⁽¹⁰⁾ that are important for DREAMO out of those factors that have an influence on general microalgae culture. Important factors include nutrient salts, culture solution (broth) stirring, culture solution (water) temperature, and light.

Regarding nutrient salts, it is possible to control microalgae production volume⁽¹¹⁾ by varying the concentrations of nutrient components. Consequently, how to set those concentrations is an important issue.

Culture solution stirring is an important factor in terms of suppressing the inhibition of production caused by the spontaneous sedimentation of DREAMO.

The culture solution temperature also has an effect on decreasing algae production volume and reduction of ecological activity. Figure 4 shows the results from tests of the production volume per week. These indicate that the optimal DREAMO temperature is in the range from 20°C to 35°C, and the limit temperature for not inhibiting growth is 40°C. In the low-temperature range, it is clear that production volume decreases at or under 10°C. In order to realize stable culture, therefore, control of the culture solution temperature to keep it in the range between 10°C and 35°C is an issue.

Light is the energy source for photosynthetic reaction, and as the intensity of the light cannot be readily increased, it is important to consider directing a greater amount of light onto the algae.

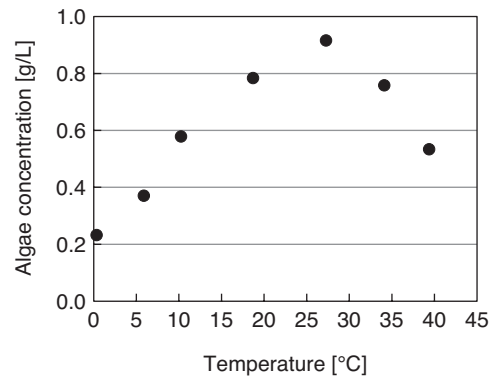


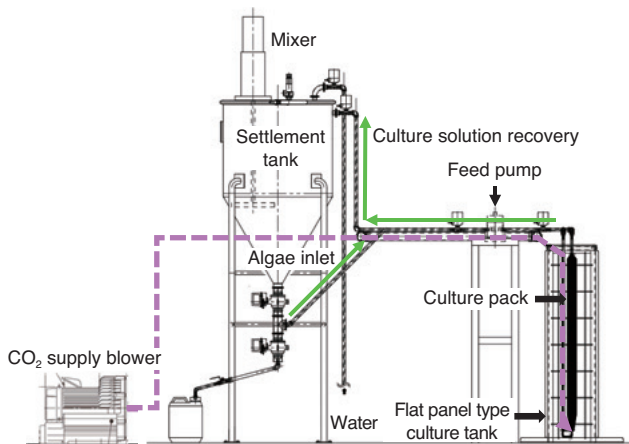
Fig. 4 Temperature dependence of DREAMO production

3. Development Goals

This research used the proprietary DREAMO developed at Honda and the flat panel photobioreactor to investigate the following items.

- (1) Microalgae culturing conditions (proportions of nutrient salts and culture solution stirring speed)
- (2) Culture tank structure to enable temperature control and the greatest possible amount of incident light

The raw material for bioethanol comes mainly from

Fig. 3 Ancillary equipment for harvesting and CO₂ supplying

corn and sugarcane. Ethanol production from sugarcane has a capacity per planted area that is three times greater than corn⁽¹²⁾ and is known to be more highly efficient than corn. The target value for the present research was therefore set as 10.0 g/m²/day (equivalent per occupied area), which is the amount of microalgae necessary in order to achieve efficiency that is on a par with ethanol from sugarcane, which has a production volume of 11.2 m³/ha/year⁽¹²⁾.

4. Investigation of Microalgae Culturing Conditions

4.1. Investigation of Nutrient Salts

Elements such as nitrogen (N), phosphorus (P), potassium (K), and so on are among the important nutrients in microalgae culture. Phosphorus is used in the form of adenosine tri-phosphate (ATP), which provides the energy in metabolic reactions. Potassium and other such minerals act to supplement chemical reactions inside cells, playing an important part in metabolic reactions. On the other hand, nitrogen is one of the important components that make up cells, and it regulates the culture medium⁽⁷⁾ that has already been optimized. This research investigated phosphate and potassium concentrations that are suited to DREAMO culture.

The components of the culture solution that serves as a base are shown in Table 2. Phosphorus and potassium make up the phosphate culture medium. The investigation thus sought to determine phosphorus and potassium concentrations that would yield the greatest DREAMO production volume using the potassium phosphate concentration as a benchmark and without changing the phosphorus/potassium ratio. The test conditions and test results are shown in Table 3 and Fig. 5, respectively. When potassium phosphate is at 2,000 ppm or lower, decreasing potassium phosphate concentration is accompanied by diminishing production volume. On the other hand, when the potassium phosphate concentration is at 2,000 ppm or above, production volume remains flat, so a potassium phosphate concentration of 2,000 ppm was set as the lower limit value.

4.2. Investigation of Culture Solution Stirring Conditions

Investigation of culture solution stirring suited to DREAMO production was carried out with the flow-field velocity of the culture solution as an index. The flow-field velocity requirements are set according to the relationship between flow-field velocity and photosynthesis efficiency (PE), which is an index of DREAMO production efficiency. As shown in Eq. (1), the PE is defined as the proportion of the energy equivalent value of DREAMO production volume and the amount of light received during the culture period.

$$\text{PE [\%]} = \frac{\text{DREAMO production volume [MJ/m}^2\text{/day]}}{\text{Photosynthetically active light energy [MJ/m}^2\text{/day]}} \quad (1)$$

The aim in raising culture solution stirrability is to suppress spontaneous sedimentation and thereby suppress

Table 2 Nutrient components of culture solution

Stock liquid	Chemical formula
UREA	CH ₄ N ₂ O
	MgSO ₄ ·7H ₂ O
	CaCl ₂ ·2H ₂ O
Phosphate	K ₂ HPO ₄
	KH ₂ PO ₄
Hutner's trace elements	ZnSO ₄ ·7H ₂ O
	H ₃ BO ₃
	MnCl ₂ ·4H ₂ O
	FeSO ₄ ·7H ₂ O
	CuSO ₄ ·5H ₂ O
	(NH ₄) ₆ Mo ₇ O ₂₄ ·4H ₂ O

Table 3 Typical conditions for lab-scale DREAMO culture

Factor	Unit	Value
Water temperature	[°C]	28
Incident light	[mol/day]	16
Light irradiation time	[hour-light / hour-dark]	10 / 14
Air-CO ₂ mixed gas airflow	[vvm]	0.15
CO ₂ concentration	[%]	5
Amount of culture medium	[L]	2

the inhibition of DREAMO production. In order to achieve the target algae production volume, the PE enhancement effect was allocated to each item for implementation, and it was found from the results that PE enhancement of 3.2% from stirring would be sufficient.

The flow field velocity of the culture solution was visibly quantified using the particle image velocimetry (PIV) method. Measurement was made by simulation of a culture tank, as shown in the photographs in Fig. 6, using a culture container (b) assembled with a flow guide (a). This was done using tracer particles of a specific weight and size equal to DREAMO in the culture solution. In the course

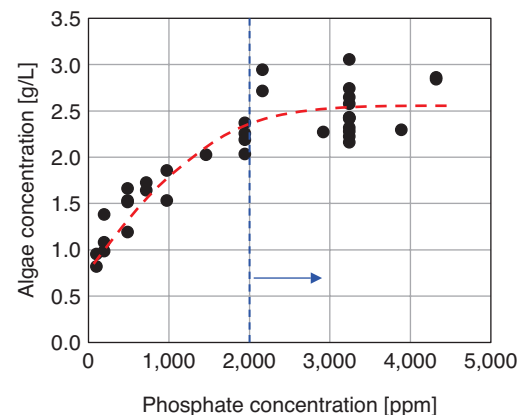


Fig. 5 Phosphate dependence of DREAMO production

of measurement, gas aeration and stirring of the tracer particles were performed. Particle velocities in the X-axis and Z-axis directions were measured by high-speed camera. It was anticipated that there would be variations in velocity inside the container as a result of the influence of bubble diffusivity due to water levels, and measurements were made in the height direction at three locations as enclosed by the red square in Fig. 7.

The relationship between the average velocity inside the culture container obtained by the above measurements and the PE enhancement margin is shown in Fig. 8. It was confirmed that when the necessary flow field velocity was 0.02 m/sec or greater, the PE would be enhanced by 3.2% or more.

Next, the culture solution stirring structure was investigated for the requirement of a flow field velocity of 0.02 m/sec.

The two types of guide shape shown in Figs. 9(a) and 9(b) were investigated. Both proposed shapes supplied gas from the bottom of the culture pack to the inside of the flow guide, placing an upward velocity through the flow guide to create a flow in the culture solution. Shape (a) is structured

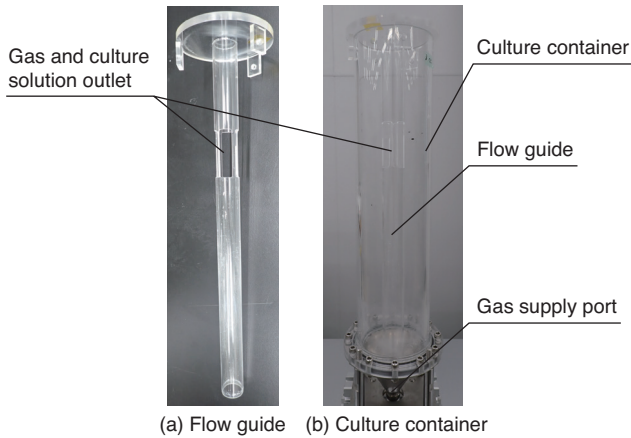


Fig. 6 Simulated culture tank test container

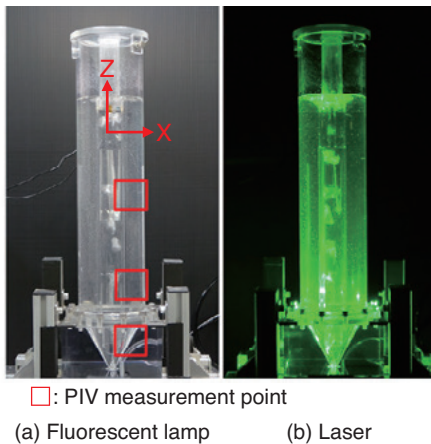


Fig. 7 Flow velocity measurement by (a) and (b)

so that gas and liquid are discharged perpendicularly to the culture tank installation surface. The aim of this structure is to create leftward and rightward flows from the installed flow guide in the middle. Shape (b) is structured so that gas and liquid are discharged in a single direction. The aim here is to increase the flow velocity by causing the flow to go in a single direction.

The flow field velocities when using flow guide shapes (a) and (b) were predicted by computational fluid dynamics (CFD) using the Fluent solver from Ansys, Inc. This simulation predicts the flow field for the culture tank as a whole. It reflects the body force of the culture solution due to the air-lift, obtained by the PIV method, that has the gas supply as its driving force, together with the dispersibility of particles of the same specific weight and size as the algae.

Figure 10 shows the results from simulation of guide shapes (a) and (b). The flow velocity due to the air-lift inside the flow guide is 0.10 m/sec or higher. With shape (a), the only location where that flow velocity could be maintained was in the vicinity of the flow guide gas supply port. The flow velocities around the base of the culture pack and at the back of the guide were found to be extremely low. However, shape (b) was found to be able to maintain the

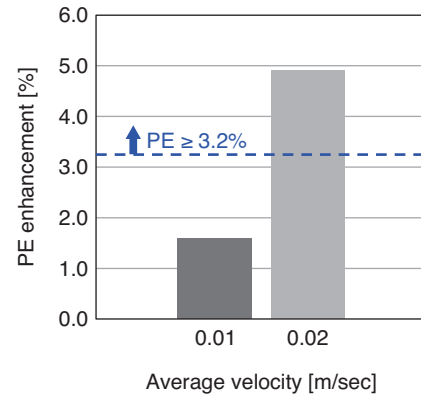


Fig. 8 Relationship between flow velocity and PE

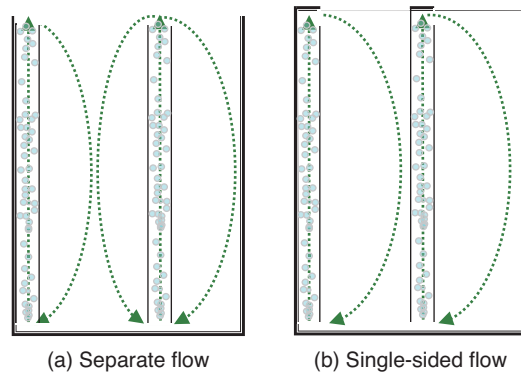


Fig. 9 Guide shape designs to make flows (a) and (b) in culture tank perpendicular to gas exhaust port

flow velocity in the culture pack as a whole. This is thought to occur because the supply ports for water and gas from the flow guide are oriented in a single direction so that the flow velocity due to air-lift is not dispersed and stirring occurs without reduction in the flow velocity. Given the above results, shape (b) was chosen for the flow guide shape.

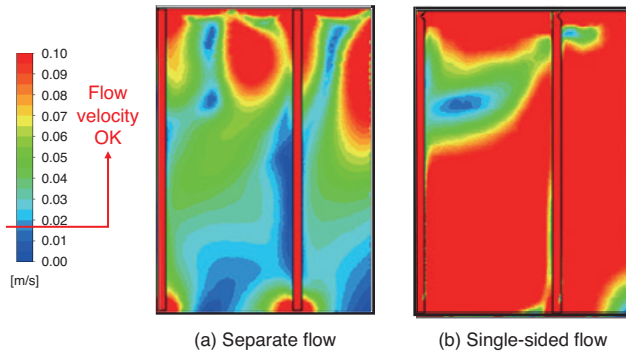


Fig. 10 Results of culture fluid flow simulations for guide shape effect

5. Investigation of Culture Tank Structure

5.1. Temperature Retention Due to Thermal Insulation Layer Structure

The control temperature for DREAMO culture is known to be from 10°C to 35°C. Culture tank structure that enables control within the control temperature range was investigated.

The culture solution temperature performance of the flat panel photobioreactor is shown in Fig. 11. For summer verification, this testing was carried out in Okinawa, where Japan has high insolation and outdoor temperatures. For winter, it was carried out in the northern Kanto region, where the temperatures drop below freezing.

In the summer, the control temperature was confirmed to be at or below the upper limit value of 35°C. On the low-temperature side, however, there was a large difference from the control temperature. A device structure that would raise the culture solution temperature by making use of solar energy was therefore investigated.

The method, as shown in Fig. 12, was a structure that maintains the culture solution temperature by adding a thermal insulation layer around the culture tank.

For the thermal insulating effect, the insolation⁽¹³⁾ and outside air temperature⁽¹⁴⁾ data provided by the New Energy and Industrial Technology Development Organization (NEDO) was used to calculate the annual temperature of the culture solution⁽¹⁵⁾. Changes were made to the culture solution temperature to reflect the heat input from solar energy together with the amount of heat released into the air and the ground surface in each time period. The rate of heat release into the outside air and some other such coefficients

reflect measurements made with the culture tank installed outdoors.

Figure 13 shows the annual predicted culture solution temperature. The thermal insulating structure was attached from October to March and removed from April to September. This yielded the expectation that the temperature could be kept within the control temperature range throughout the year.

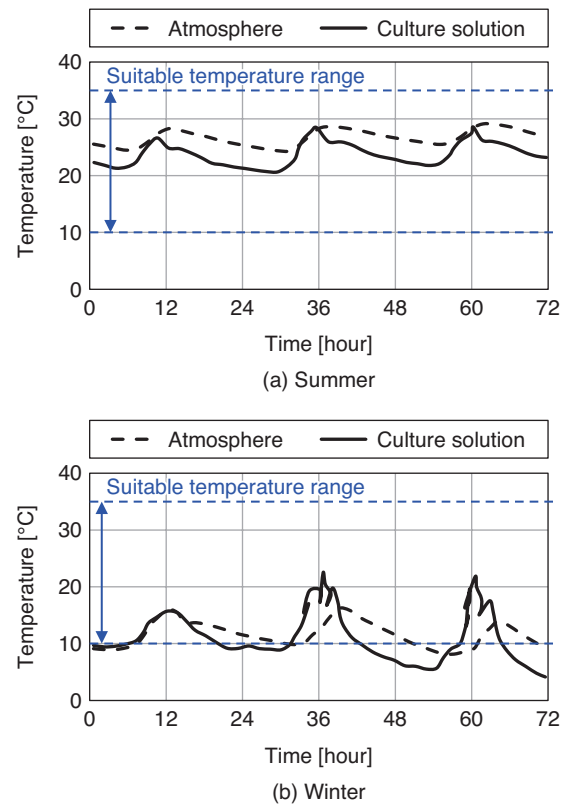


Fig. 11 Temperatures of culture tank culture solution and ambient air measured in summer and winter

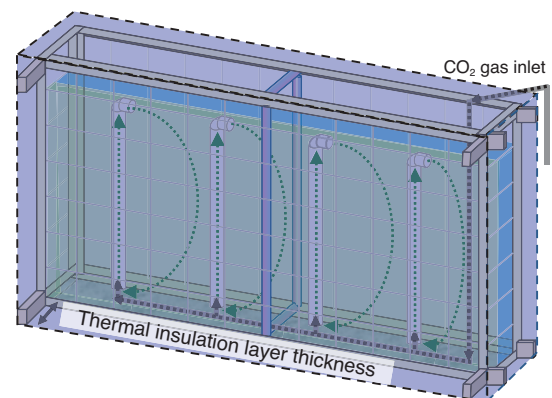


Fig. 12 Schematic representation of flat panel culture tank with heat insulating layer

5.2. Culture Tank Structure that Increases the Amount of Incident Light

Light is the source of energy for photosynthetic reaction, and a culture tank structure that would increase the amount of incident light was investigated.

The requirement for the amount of light was set at 20 mol/day or more as the necessary amount of light calculated from the target DREAMO production volume.

Figure 14 shows the path of incident light and the amount of light loss up to when solar energy is received by the DREAMO. The amount of light is determined by the area of culture tank installed and the culture tank height. The culture tanks were also placed at uniform intervals (below, separation distance) in order for each culture tank to have equal light exposure. For this study, a fixed separation distance was made a precondition. As shown by the proposed structures for investigation in Fig. 15, two models were investigated, one structure (a) with a reflector installed on the culture tank and another structure (b) that has the culture tank installed at an angle (below, a tilt).

Structure (a) has the reflector installed at the front surface (south side) of the culture tank. It is a structure that directs incident light at the culture tank by reflecting the

light received within the separation distance. Structure (b) places the culture tank itself at a tilt. It is a structure that aims to increase the light intake efficiency of the culture tank. Both structures were considered at angle levels of 30°, 45°, and 60°.

The amount of light received by each culture tank structure was investigated using light simulation. OpticStudio from Zemax was used and the solar orbit with respect to the installed culture tank based on the solar altitude and the change in time per day from sunrise to sunset according to the season was incorporated in the model to predict the amount of incident light on the surface of the culture pack. The simulation conditions for this investigation are shown in Table 4 and Fig. 16. The light source was defined as 1 sun as used in solar cell performance evaluation standards. The solar altitude and orientation as affected by the season and time⁽¹⁶⁾ were incorporated into the model for the assumed culture tank installation location in Utsunomiya City, Tochigi Prefecture, Japan.

Figure 17 shows the results of simulations conducted for structures (a) and (b). The tilt structure in which the

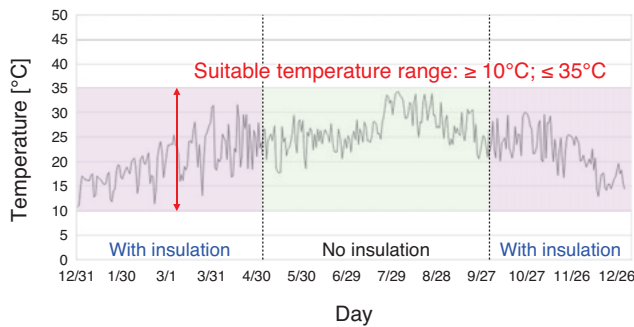


Fig. 13 Estimated annual temperatures of culture solution in North Kanto region with thermal insulation for winter period considered

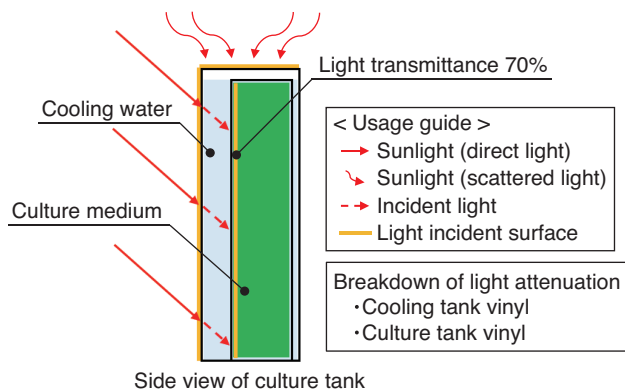
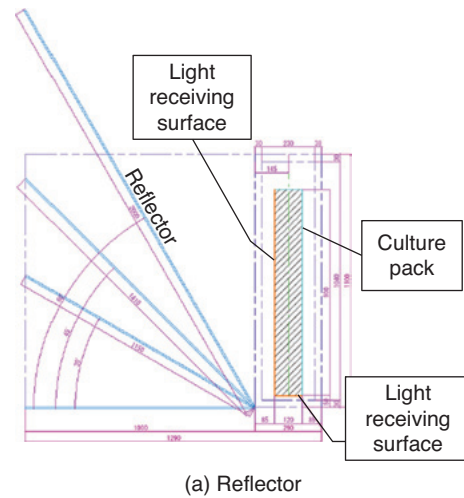
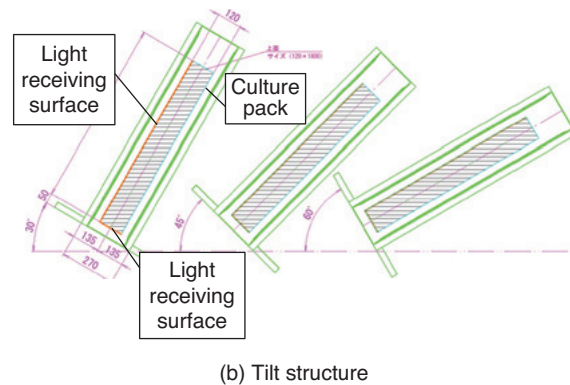


Fig. 14 Schematic representation of light loss caused by culture medium and culture tank structure



(a) Reflector



(b) Tilt structure

Fig. 15 Schematic representation of simulation models used for estimation of effects of (a) and (b) on flat panel photobioreactor

Table 4 Basic shape, light source, and incident light conditions for simulation model

Factor	Unit	Value
Simulation software	[-]	Zemax OpticStudio
Housing conditions		
Housing size	[mm]	L 1,800 × W 210 × H 1,000
Separation distance	[mm]	1,000
Light loss conditions		
Light transmittance	[%]	72.3
Solar conditions		
Light source	[Sun] (W/m ²)	1 (1,000)
Direct light	[%]	70
Scattered light	[%]	30

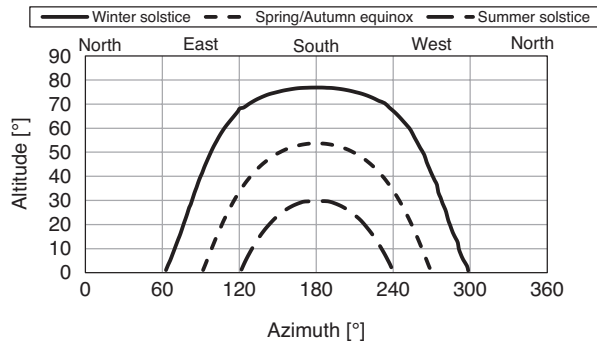
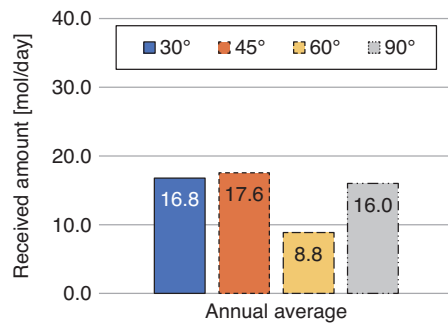
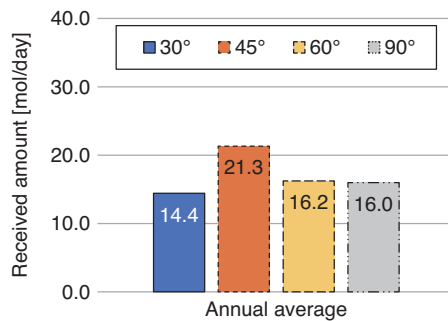


Fig. 16 Sun orientation and altitude used for optical simulations for spring and autumn, summer, and winter conditions



(a) Reflector



(b) Tilt structure

Fig. 17 Estimation of effects of (a) and (b) to enhance incident light on culture tank surface

culture tank itself is installed at an angle received the greatest amount of light under the 45° condition. This was found to exceed the target of 20 mol/day.

6. Enhanced DREAMO Production Volume Results

Outdoor culture of DREAMO was carried out in Tochigi Prefecture, as shown in Fig. 18, reflecting the optimization of nutrient salt component concentrations and the results from investigation of culture solution flow guides. Figure 19 shows the average annual production volume (a) calculated from these test results and the estimated value for annual average production volume (b) when the effects of the thermal insulating structure and tilt structure are included. The configured culturing conditions yielded a production volume of 8.6 g/m²/day. In addition, the verification results described above yielded the prospect that production volume of 13.5 g/m²/day which exceeded the target of 10.0 g/m²/day could be obtained by using a thermal insulating layer structure on the culture tank to keep it within the culturing temperature control range and by using a tilt structure to increase the amount of light received on the culture tank.



Fig. 18 Flat panel photobioreactors placed outdoors

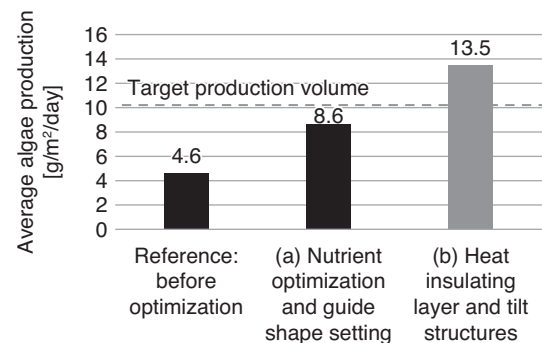


Fig. 19 Results of annual production of DREAMO estimated from outdoor experiments and public climate database

7. Conclusion

DREAMO and a flat panel photobioreactor were used to conduct an investigation of the optimization of culturing conditions and of the culture tank structure with the objective of creating technology for outdoor stable culture in large quantities. The following results were obtained.

- (1) Production volume was increased under culturing conditions by optimizing the concentrations of nutrient salt components phosphorus and potassium.

In addition, by raising the flow field velocity of the culture solution to 0.02 m/sec or higher and adopting a flow guide shape that discharges liquid and gas in a single direction, efficiency was enhanced and production volume increased.

- (2) It was verified that by adoption of the thermal insulating layer structure, the culture tank temperature is controllable to within the control range throughout the year even in Tochigi Prefecture. This verified that culturing can be conducted without the growth of DREAMO being inhibited. In addition, installing the culture tank with a 45° tilt made it possible to increase the amount of incident light received by the culture tank.

Based on the outdoor culture tests reflecting the above findings and culture tank structure, prospects for a DREAMO production volume of 13.5 g/m²/day were gained.

This indicated the possibility that DREAMO could achieve ethanol production volume per planted area that is equal to or better than that of bioethanol from sugarcane, which is a carbon neutral fuel.

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Semi-physical Model that Predicts Internal State of Lithium-ion Batteries and Calculates Degradation Behavior with High Accuracy

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ABSTRACT

A degradation simulation model based on the mechanism of lithium-ion rechargeable battery performance expression was developed in order to predict the long-term durability of on-board lithium-ion rechargeable batteries with high accuracy. Up to now, guaranteeing the long-term durability of lithium-ion rechargeable batteries required correspondingly long-term testing and design values with a large margin in terms of prediction accuracy. In the developed model, the model portion that calculates the battery performance was made into a physical model using the physical quantities that influence the degradation mechanism as explanatory variables, and the degradation behavior of each factor was made into an empirical model that is trained from the test results. The model with this hybrid structure was proposed as a semi-physical model. As a result of this, accuracy in predicting durability was increased, and a capability to represent the non-linear behavior of performance degradation transition over long periods of time was indicated. When the internal state of that model is to be acquired by disassembly analysis, however, model training incurs a high development cost. For this investigation, therefore, the approach of determining the internal state by calculation from voltage and current data was chosen rather than that of disassembling lithium-ion rechargeable batteries to measure their internal state. This choice was also intended to increase the applicability of the approach by reducing the training cost. In this way, it becomes possible to reduce the size of the extra margin necessary in design as well as to enhance convenience.

1. Introduction

Because of the high energy density of lithium-ion rechargeable batteries (LiB), there has been an increased need in recent years for these batteries as the power source for electric vehicles in the move toward a decarbonized society⁽¹⁾⁻⁽³⁾. Long-term durability performance of 10 years or more is sought for on-board LiB⁽¹⁾. The LiB performance degradation transition over the long term sometimes displays non-linear behavior that diverges from its linear behavior with respect to the power of the time period and number of charge-discharge cycles. Accurately predicting the prospects for that durability is no simple matter (Fig. 1)^{(4),(5)}. As to why the LiB performance degradation transition is non-linear, the reasoning here is that it may be because the multiple factors that cause expression of LiB performance differ one from the other in their degradation

behavior with respect to their elapsed time^{(4),(6)}. Generally, LiB performance degradation is predicted using methods that extrapolate it empirically using acquired data, or methods (acceleration tests) that shorten the time taken to

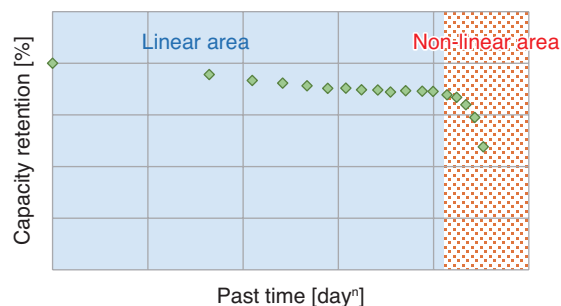


Fig. 1 Degradation transition into non-linearity

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confirm degradation behavior according to the intensity of degradation factors such as temperature and state of charge (SOC)^{(7),(8)}. In the former case, making long-term predictions with empirical models that have been trained using training data from a brief training period risks diminishing the reliability of the prediction results^{(3),(4),(9)}. Also, in the latter case, the balance of degradation between multiple factors of LiB performance expression changes, so that a simple acceleration of aging time is not achieved, and the degradation outlook cannot be readily judged, as has been previously suggested⁽¹⁰⁾. In order to address these risks, development would require a long development period and a large margin for durability design.

Meanwhile, research sought to address those issues by taking up physical models based on physical phenomena⁽¹¹⁾. These have the following two issues, however, so they are not purely physical models⁽⁹⁾. The first issue is that model training requires values for the physical properties involved, such as electrode plate thickness and electrolyte salinity. For that reason, users who did not design and manufacture the LiB cannot readily acquire those items of information, and creation of a model is no easy matter. The second issue is that because the principle formula is for an ideal state, it often does not match actual behavior. For this reason, the model formula uses correction factors that adjust for those differences, and the various behaviors are expressed by similar figures.

For the present research, therefore, a solution to these issues was sought by proposing a semi-physical model⁽⁴⁾ that makes the model portion that calculates LiB performance based on the factors in LiB performance expression into a physical model and makes degradation behavior in those various expressions into an empirical model that is trained from the test results. In this paper, Chapter 2 below will discuss a degradation simulation model that makes it possible to represent non-linear degradation behavior; Chapter 3 will describe that model's training method and accuracy verification results; and Chapter 4 will describe discussion using model technology in acceleration tests by means of heating.

2. Creation of a Degradation Simulation Model

2.1. Degradation Model Aims and Concept

The method of creating the semi-physical model will be described. First, the performance expression mechanism portion that is not dependent on the materials used in the LiB or on its design values is treated as a physical model portion. Next, the factor portion that is dependent on materials used and design values is treated as the empirical model portion that is trained mathematically on the basis of test results. For the empirical model training, the behavior of change with respect to the loads that are causes of degradation is measured for each of those factors by durability tests and used as training data for training

the model. By empirical model training in the degradation behavior for each factor, those portions that do not fit with a theoretical, ideal state can be made correctable, and since it does not require values for the various physical properties that are necessary to the physical model, its applicability can be heightened by comparison with the physical model. In addition, when attention is focused on each LiB performance expression factor, those factors are found to be single mechanisms and they display linear degradation transitions according to their respective theories. For example, the growth behavior of the solid electrolyte interphase (SEI) membrane that forms on the surface of the anode material and the electrolyte interface follows the square root law⁽¹²⁾. Consequently, predictions in regions that extend into longer times than the training data can be estimated with only slight deviation by straight-line extrapolation from the square root of the time. By these approaches, it becomes possible to represent non-linear degradation behavior with respect to time and charge-discharge cycles. Since LiB performance is expressed by a combination of multiple factors, cases where a single factor dominates degradation behavior indicate linear degradation. However, when that dominant factor switches over to another factor, then the degradation behavior is non-linear. For this reason, non-linear degradation behavior can be represented if performance expression factors are modeled individually and performance is calculated from the combination of factors based on their mechanisms. Since degradation is estimated virtually by calculation, it also becomes possible to remove the time constraint in investigations as compared to tests.

Changes in the LiB performance expression factors that become explanatory variables in the model are generally measured by disassembly analysis. With this kind of method, further durability tests of a sample cannot be conducted beyond the point when it has been disassembled. Consequently, training for one degradation transition behavior necessitates causing degradation of multiple samples under the same conditions, and fabricating samples in which degradation advances differently. For this method, acquiring training data necessitates many samples and many analyses. For the present investigation, therefore, an approach by analysis with current and voltage data that can be acquired without disassembling a battery was implemented.

2.2. Simulation Model Structure

2.2.1. Rated capacity model

In this clause, the configuration of a rated capacity model based on the expression mechanism for capacity will be explained. Figure 2 shows a conceptual diagram of the LiB rated capacity expression mechanism and calculation. As shown in the figure, expression of the rated capacity involves the relationship of the following four explanatory variables. By following this relationship, the rated capacity can be calculated⁽¹³⁾.

- (A) Cathode Ah-Open Circuit Potential (Ah-OCP) curve
- (B) Anode Ah-OCP curve
- (C) $OCV_{\max}$ [V]
- (D) $OCV_{\min}$ [V]

In other words, degradation of the rated capacity can be defined as occurring by means of changes in these variables (A)-(D). For this investigation, training in the change behavior in these variables (A)-(D) is carried out empirically. However, (C) can be defined as a voltage that is determined by the specifications, so here it was handled as a constant. The variable (D) is the open circuit voltage (OCV) for the current that is determined by the specifications that occurs when the LiB is discharged with a constant current up to the voltage similarly determined in the specifications, and its value changes under aging conditions in conjunction with the degradation of LiB internal resistance. For this investigation, therefore, $OCV_{\min}$ was taken as a function of the LiB internal resistance that accompanies degradation. The $OCV_{\min(t)}$ model formula isolates the resistance component ($R_{IMP(t)}$) of the frequency where the change from the initial value ($OCV_{\min(t_0)}$) has the highest correlation with the impedance (IMP) obtained from the cell and models it in Eq. (1)⁽¹³⁾. $R_{IMP(t)}$ in Eq. (1) is given according to the calculation results from the internal resistance model, which will be described later. In the equation, d is a correction factor that is learned in order to make $R_{IMP(t)}$ agree with the measured $OCV_{\min(t)}$ in Eq. (1).

$$OCV_{\min(t)} = OCV_{\min(t_0)} + d \times R_{IMP(t)} \quad (1)$$

For this investigation, the Ah axis of Ah-OCP is represented as the standard 0 Ah at the initial time of 0% SOC, which is represented as the basis Ah. From this it is possible to represent the rated capacity by the relationship in Eq. (2) below.

$$\text{Rated capacity}_{(t)} = f(\text{Cathode Ah-OCP curve}_{(t)}, \text{Anode Ah-OCP curve}_{(t)}, OCV_{\max}, OCV_{\min(t)}) \quad (2)$$

For the rated capacity_(t) at time t , the LiB characteristic

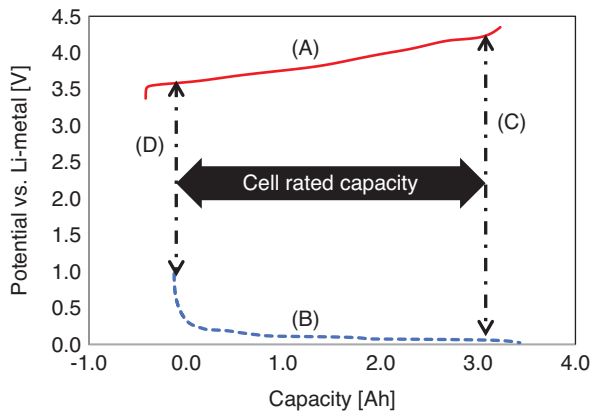


Fig. 2 Mechanism of capacity calculation

of Ah-OCV is determined from the combination of the electrical characteristic of the cathode (cathode Ah-OCP curve_(t)) and of the anode (anode Ah-OCP curve_(t)) at that same time. In addition, the Ah range that can be used as the LiB rated capacity is calculated from the OCV ($OCV_{\max}$) at 100% SOC and the OCV ($OCV_{\min(t)}$) at 0% SOC calculated from Eq. (1).

The change in variable (A) that accompanies degradation is represented by changing the basis Ah axis by multiplying that initial (A) by the capacity retention of the cathode. When changing the Ah-OCP curve, the respective electric potential positions of the cathode and anode according to the cell voltage during aging are fixed in place in the basis Ah axis direction, and the Ah-OCP curve profile is changed in the basis Ah axis direction (Fig. 3). Variable (B) also has changes made to it, as done with (A), by the anode capacity retention, in addition to which the anode Ah-OCP curve shifts to the higher-potential side with respect to the cathode Ah-OCP curve (the anode Ah shift) because of a side reaction of SEI formation, and variable (B) after degradation was represented by a parallel shift of the anode Ah-OCP curve with respect to the basis Ah axis⁽⁴⁾ (Fig. 4).

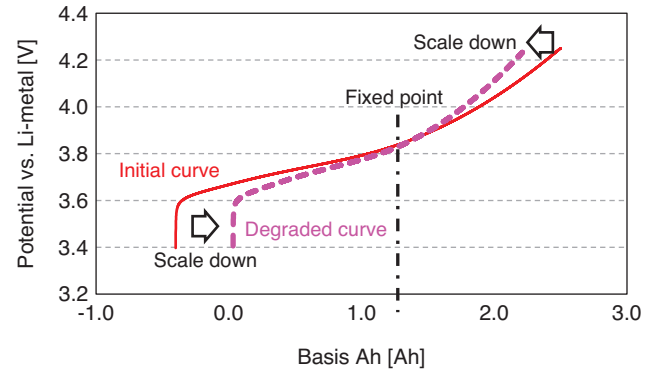


Fig. 3 Calculation of aging cathode curve

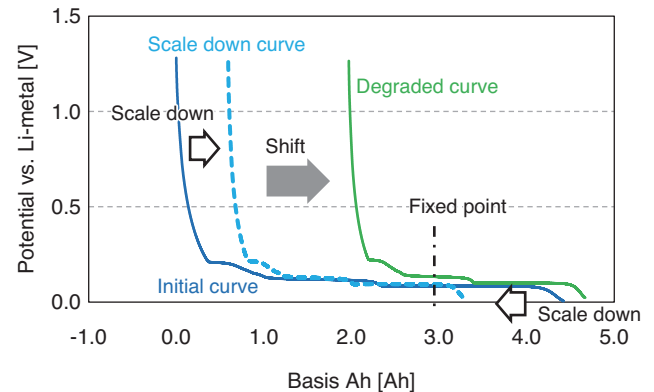


Fig. 4 Calculation of aging anode curve

2.2.2. Internal resistance model

In this clause, the configuration of a rated capacity model based on the expression mechanism for internal resistance will be explained. Figure 5 shows a conceptual diagram of the LiB internal resistance expression mechanism by means of a schematic cross-section of a cell. The LiB internal resistance is expressed by a combination of multiple components, and when power is supplied, internal resistance is generated from electron transfer (i)(viii), lithium ion insertion-extraction reaction (ii)(vii), and lithium ion diffusion migration (iii)-(vi) respectively, in that order.

For this investigation, LiB internal resistance is represented by the equivalent circuit shown in Fig. 6, and the following six items were treated as explanatory variables⁽¹⁴⁾.

- (R_0) Electron conduction resistance and ion conduction resistance [Ω]
- (R_1) Resistance component of anode reaction resistance [Ω]
- (CPE_1) Electric double-layer component of anode reaction resistance
- (R_2) Resistance component of cathode reaction resistance [Ω]
- (CPE_2) Electric double-layer component of cathode reaction resistance
- (CPE_3) Diffusion resistance

The sum of the resistances expressed by these six components is the internal resistance of the LiB. Its degradation occurs with the change of these components, similar to what is described in Clause 2.2.1. The six

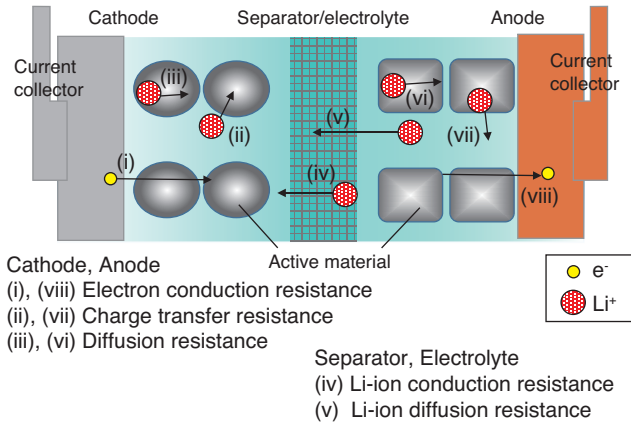


Fig. 5 Mechanism of internal resistance calculation

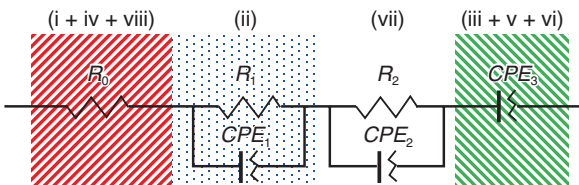


Fig. 6 Equivalent circuit of internal resistance

resistances are dependent on how long power is supplied, and since they can be represented by functions for the time power is supplied using the equivalent circuits, the calculation of the internal resistance of the LiB as a whole from their combination is performed as a physical calculation. On the other hand, the internal resistances that are treated as explanatory variables are trained empirically in change behavior acquired through tests. Having a modeled structure for each internal resistance component makes it possible to represent the changes in time dependency of reaction resistance and diffusion resistance in the cathode and anode accompanying degradation, and this has made it possible to estimate internal resistance with greater accuracy.

Internal resistance is generally evaluated by direct current resistance (DCR) that is calculated from the slope of the current-voltage (I-V) characteristic. For this model, therefore, it is output as a quantity converted to DCR from the equivalent circuit in Fig. 6. Due to the circumstances of the method for evaluating the I-V characteristic, it measures not only a pure resistance value, but also the change in OCV that accompanies the supply of power. For this model, therefore, the change in OCV that accompanies the change in SOC when power is supplied was also included, in addition to the overvoltage, in calculating the closed circuit voltage (CCV) that is generated by the application of current. By using the calculation results described above in Clause 2.2.1., the change in OCV (ΔOCV) that accompanies the change in the charge amount due to the supply of power was calculated, the I-V characteristic was calculated from the sum (ΔV_{total}) with overvoltage (ΔV) due to internal resistance, and in this way the accurate DCR was calculated (Fig. 7). In addition, the overvoltage (ΔV) due to internal resistance was calculated [Eq. (3)] by solving it as a function of time (t) from the equivalent circuits in Fig. 6⁽¹³⁾.

$$CCV = OCV - I \times \left[R_0 + R_1 \times \left\{ 1 - \exp \left(\frac{-t}{R_1 \times C_1} \right) \right\} + R_2 \times \left\{ 1 - \exp \left(\frac{-t}{R_2 \times C_2} \right) \right\} + \frac{t^{CPE_3}}{CPE_{3-T} \times CPE_{3-p}!} \right] + \Delta OCV \quad (3)$$

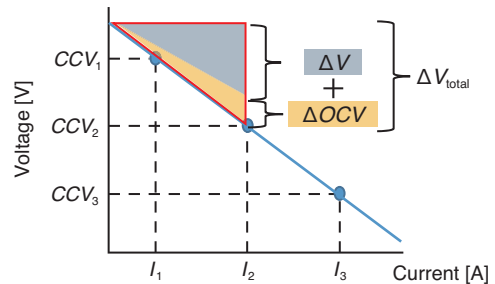


Fig. 7 How to calculate I-V characteristics

CPE has the T value that represents the electric double-layer capacity and the p value that represents the state of collapse of arcs in the Nyquist plot. Therefore, those values in CPE_n ($n = 1 - 3$) are indicated in the equation by CPE_{n-T} and CPE_{n-p} .

When calculating the transient voltage response that accompanies the application of current, the calculation cannot be done using the parallel circuits with CPE and R used in the equivalent circuits in Fig. 6. Therefore, Eq. (4) was used to convert CPE_n and the resistance component R_n connected in parallel with it into C_n and perform the transient response calculation.

$$C_n = CPE_{n-T} \frac{1}{CPE_{n-p}} \times R_n \frac{1 - CPE_{n-p}}{CPE_{n-p}} \quad (4)$$

3. Model Training and Simulation Results

3.1. Training Method

In this chapter, an overview will be given of the training method used for the empirical model portion. For this investigation, a single-factor experimental method based on experimental design was applied to conduct durability tests by multiple standards of each factor that influences degradation and acquire training data⁽¹⁵⁾. The durability tests were conducted with load conditions other than degradation factors corresponding to explanatory variables taken as constants. The LiB degradation factors assumed for the present investigation are shown in Table 1.

The method of analysis by non-disassembly used to isolate the explanatory variables for each model will be described later in the respective clauses. The degradation behavior of each explanatory variable acquired was fitted to below candidate equations Eqs. (5) and (6) and the better fit was selected.

$$y = a \times x^b + c \quad (5)$$

$$y = a \times \ln(x) + c \quad (6)$$

For this, a was derived for each durability condition and b for conditions of resting degradation and of degradation of the supply of power, deriving them as a constant with a single common value for each explanatory variable respectively. Next, the derived coefficient a was a curved surface fitted on a multidimensional surface that has the number of degradation factors as the number of dimensions and a map of degradation coefficients was created. For this investigation, durability tests for the purpose of model training had a load applied for a durability period of four months and the two months necessary for measuring performance changes occurring during that time, making a total of six months. Performance measurements were made at the start of aging and then during aging in the first week, the second week, the fourth week, and at four-week intervals thereafter, a total of eight times.

Table 1 List of degradation factors

Factor		Degradation factor
Rated capacity	Cathode capacity	Temperature, Average cathode SOC, Cathode SOC width, Cathode current density (Charge, Discharge)
	Anode capacity, Ah shift	Temperature, Average anode SOC, Anode SOC width, Anode current density (Charge, Discharge)
Internal resistance	R_0	Temperature, Average cell voltage, Cell voltage width, Cell current density (Charge, Discharge)
	R_1, CPE_1	Temperature, Average anode SOC, Anode SOC width, Anode current density (Charge, Discharge)
	R_2, CPE_2	Temperature, Average cathode SOC, Cathode SOC width, Cathode current density (Charge, Discharge)
	CPE_3	Temperature, Average cell voltage, Cell voltage width, Cell current density (Charge, Discharge)

3.1.1. Method of analysis of explanatory variables in rated capacity model

This clause will describe the method of analysis of each explanatory variable used in the rated capacity model⁽¹³⁾. In order to acquire the explanatory variables (A)-(D) described above in Clause 2.2.1. without disassembling a battery, dV/dQ analysis and charge-discharge curve analysis were used. The anode capacity was isolated (Fig. 8) by preparing a cell of the same specifications in its initial state in advance, removing the anode plate from it, obtaining the Ah-dV/dQ curve from that anode plate, and fitting that curve so that its peaks matched the positions of the peaks originating in the anode (arrow symbols in the figure) in the Ah-dV/dQ curve obtained from the cell.

Next, the curve of the cathode potential in the cell is calculated by subtracting the anode Ah-closed-circuit potential (CCP) curve defined in Fig. 8 from the charging curve obtained from the cell. In order to match this curve, the Ah-CCP curve of the cathode, obtained in advance as was done with the anode, is fitted with the curve, and in this way the cathode capacity was isolated. Using the cathode and anode Ah-CCP curves determined above, the Ah shift amount was isolated from the change in the Ah position in the same potential before and after aging.

3.1.2. Method of analysis of explanatory variables in internal resistance model

This clause will describe the method of analysis⁽¹⁴⁾ of each explanatory variable used in the internal resistance model.

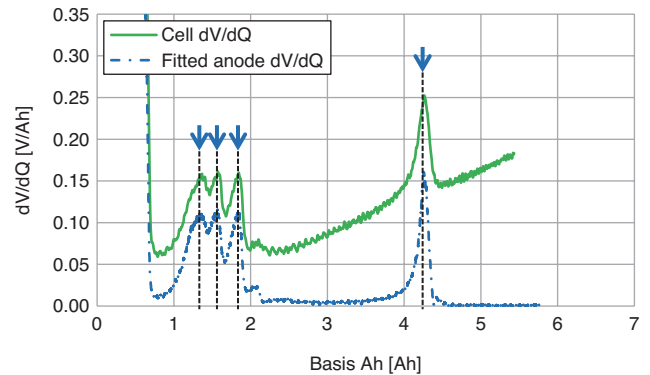


Fig. 8 Anode fitting

Generally, electrochemical impedance spectroscopy (EIS) is used as the method for separating LiB internal resistance components. With on-board LiB, however, the internal resistance values are extremely small, at several milliohms, and the expression frequencies for cathode and anode reaction resistance at normal temperatures are extremely close together. For this reason, the respective cathode and anode reaction resistances cannot readily be derived from IMP data obtained at normal temperatures. In addition, output demand is large, the current rate that flows during output is large, and the time is long. This means that the diffusion resistance component, for which the IMP is obtained in a static state by EIS, cannot be accurately acquired by that method as a dynamic value during output. For this investigation, therefore, conduction resistance (R_0) was isolated by IMP analysis using EIS at normal temperature, the individual reaction resistances (R_1 , CPE_1 , R_2 , and CPE_2) were isolated by low-temperature IMP analysis⁽¹⁶⁾, and diffusion resistance (CPE_3) was isolated by analysis of transient voltage response data acquired during I-V characteristic evaluation at normal temperature matched with the characteristics of each resistance component. The equivalent circuits shown in Fig. 6 were used to identify each resistance component. For CPE_3 , values to match the transient response for voltage with respect to applied current were derived by the least-squares method using an equivalent circuit configured with R_0 , R_1 , CPE_1 , R_2 , and CPE_2 values identified by each type of IMP analysis.

3.1.3. Simulation method

Figure 9 shows the simulation flow. The voltage and current that are the load conditions are converted from the LiB internal state at that time (t) into the loads on the cathode and anode, respectively, and provided as input

Table 2 Model formula and differential equation

	Model formula	Differential equation	
n-th power type	$y = a \times x^b + c$	$\frac{dy}{dx} = \frac{a^{1/b} \times b}{(y - 1)^{(1/b - 1)}}$	
Natural log type	$y = a \times \ln(x) + c$	$\frac{dy}{dx} = a \times e^{-(1-y/a)}$	Time model : $x = \text{time}$ Energization model: $x = \text{Ah}$

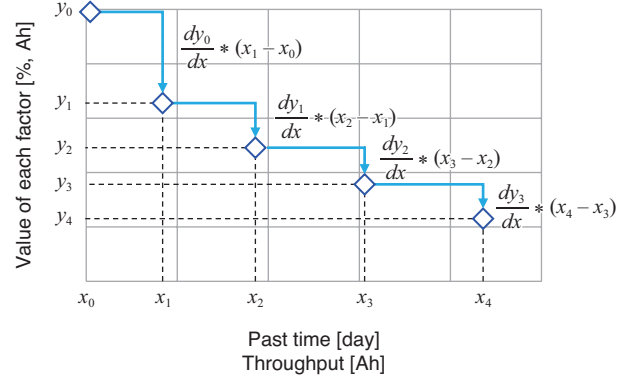


Fig. 10 Factor amount calculation method

for each model formula. The internal state is also updated with the results calculated in each model formula and the calculation for the next time ($t+1$) is carried out. The differential equation (Table 2) for calculating the amount of change per unit period that can be defined according to the model formula determined for each explanatory variable is used for each model, the coefficient a determined by the load conditions is read into it to calculate the amount of change per unit time, and those results are integrated to calculate the degradation behavior (Fig. 10)⁽¹⁵⁾.

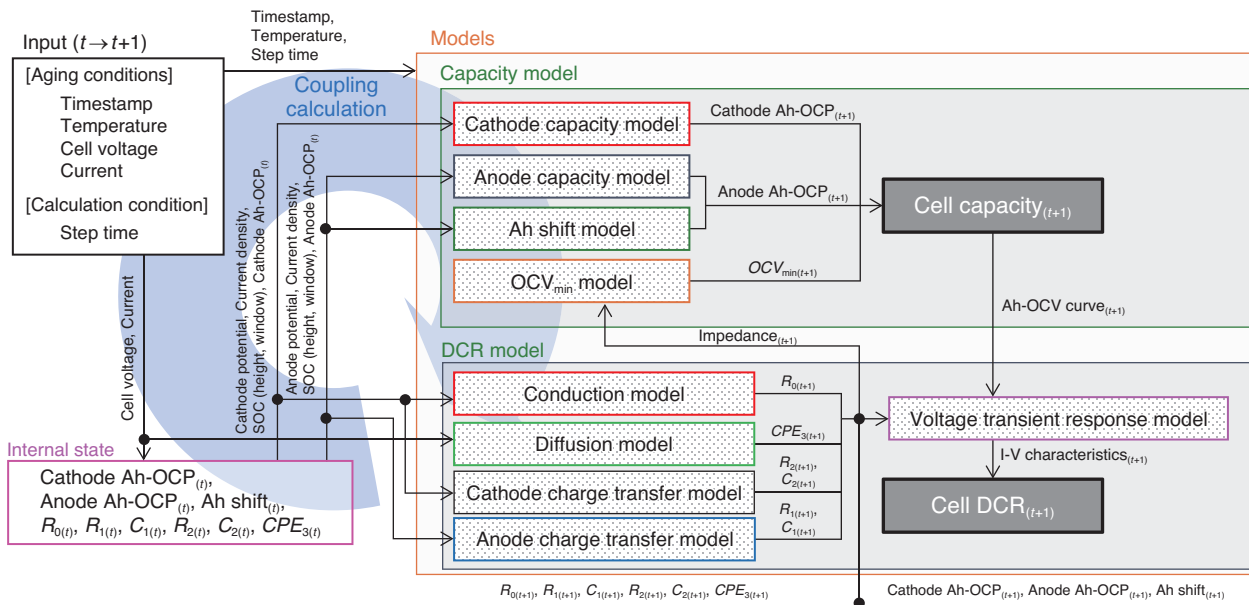


Fig. 9 Simulation flow

For degradation due to the passage of time, Miner's rule was used during the step period where degradation is added up in the simulation to calculate the degradation coefficient and basic SOC by time-weighted average. For the degradation due to supply of power, the degradation coefficient and basic SOC were calculated according to the respective pulse loads that were isolated, and the amount of change per unit section to be calculated was added up⁽¹³⁾.

3.2. Simulation Results

3.2.1. Capacity model

Figure 11 shows the results for calculation of changes in degradation during durability tests. Estimation of degradation by an empirical model (for this investigation, a power law model is used to conduct comparative evaluation) diverges from the measurement results as aging progresses, but this model achieved calculation results in line with measurement results even in the region at the end of aging where degradation is shown to be non-linear.

3.2.2. Internal resistance model

As in Clause 3.2.1., the results for calculation of changes in degradation are shown in Fig. 12. As with the capacity

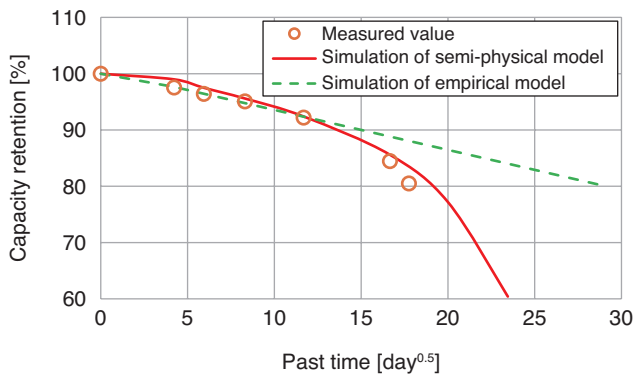


Fig. 11 Verification result of capacity model

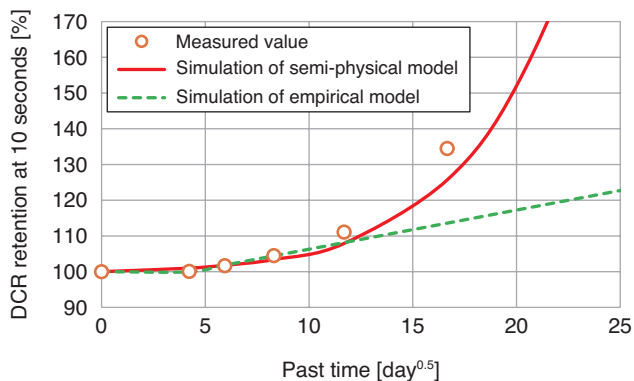


Fig. 12 Verification result of DCR model

model, this model achieved calculations in line with measurement results even at the end of aging, in contrast with the empirical model.

3.3. Conclusion

Verification results demonstrate that this simulation model has made it possible to represent non-linear behavior in the changes in degradation over the long term, which was not possible with the conventional empirical model. In addition, the condition raising the load of aging conditions successfully showed that the pattern of changes in degradation and the state of degradation inside the LiB are different.

4. Representation of Internal Degradation State under Concentration Condition

4.1. Capacity Model

Figure 13 shows a comparison of degradation behavior estimated with the model by changing only the temperature load. This was done in order to confirm differences in the state of internal degradation by acceleration tests. When changes in degradation are compared, degradation behavior under high-temperature conditions shows non-linear behavior at the time (arrow symbol in the figure) in the vicinity of 85% capacity retention where a bend occurs. At low temperature, by contrast, the bend timing does not occur and linear behavior is shown. This suggests that the same degradation pattern does not occur in acceleration testing by heating. Table 3 shows the degradation state of each factor at 60% capacity retention under both conditions. It is apparent from this that even when capacity retention is the same, the amount of degradation is different for each factor, and in the two tests with different temperatures, the degradation states are not the same. These investigation results indicate that in acceleration tests that raised the aging load, the internal degradation state and different behaviors of the patterns of changes in degradation accompanying it are possible to represent with this simulation technology.

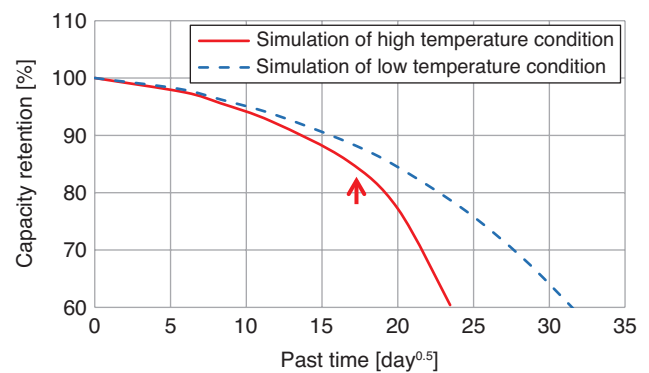


Fig. 13 Difference in capacity degradation behavior due to acceleration test

Table 3 Simulation result at capacity retention of 60%

	Aging condition	
	High temperature	Low temperature
Cathode capacity retention	85.2%	87.0%
Anode capacity retention	31.7%	59.6%
Ah shift value	0.11 Ah	0.09 Ah

Table 4 Simulation result at DCR retention of 150%

	Aging condition	
	High temperature	Low temperature
Ohmic resistance retention	100.0%	100.0%
Cathode's reaction resistance retention	111.0%	117.7%
Anode's reaction resistance retention	211.0%	179.9%
Diffusion resistance retention	181.9%	273.7%

4.2. Internal Resistance Model

As with the capacity model, the results for estimation of differences in degradation behavior in acceleration tests are shown in Fig. 14 and Table 4. In internal resistance degradation behavior, a bend occurred in the changes in degradation under both conditions, and the behavior under different timing of that occurrence (DCR retention value) was calculated (arrow symbols in Fig. 14). Table 4 shows the degradation state of each factor at the point when the DCR retention is 150% under both conditions. It is apparent from this, as with the capacity model, that even when the DCR retention is the same, the degradation state is not the same in the two tests at different temperatures.

These results indicate that even in internal resistance, there are differences in degradation behavior (Fig. 14) and the internal state after degradation (Table 4) under acceleration conditions, and that it is possible to represent those differences with this simulation technology.

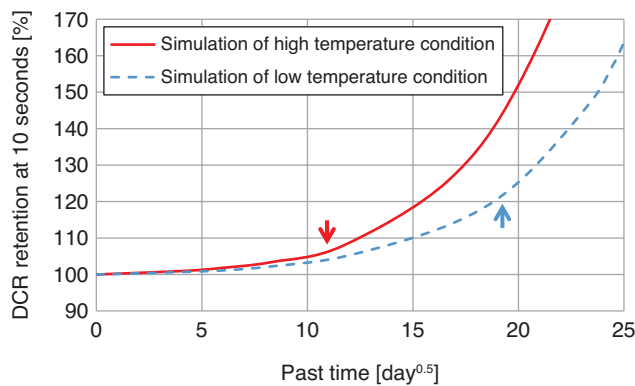


Fig. 14 Difference in capacity degradation behavior due to acceleration test

5. Summary

A semi-physical model was created that has a physical structure based on the performance expression mechanism and an empirical structure that uses data measured in tests for training. This made possible prediction of long-term degradation behavior that is highly accurate by comparison with the power law model, which is the general empirical model. In addition, this approach is capable of representing changes in degradation and grasping internal degradation states that could not be readily realized by acceleration tests with increased load, thereby suggesting that this is a method that can be used to evaluate durability performance. By the use of this technology, it becomes possible to predict the prospects for durability with accuracy in new LiB development. In addition, where up to now major constraints had been imposed on the range of usable voltage, current, and temperature in order to secure an extra margin for durability design, this technology was able to reduce these constraints, yielding the expectation of heightened convenience in terms of an expanded cruising range and an enhanced acceleration performance for electric vehicles. Moreover, this technology is applicable not only to use in development, but also to the used car market and the reuse market, where it can be applied to the diagnosis of residual value from different perspectives, not only for estimating the remaining life expectancy of a LiB over the long term, but also for matching to applications by battery life prediction that takes the internal degradation state into consideration, and so on. This technology can be expected to serve as a tool that will be able to support the widespread adoption of electric vehicles and LiB reuse.

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Study of Heat Treatment Conditions that Impact Thermal Conductivity of Aluminum Casting Alloy

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ABSTRACT

An approach was studied that sets the heat treatment conditions to increase thermal conductivity after achieving the mechanical properties demanded of aluminum casting alloy parts. The heat treatment conditions that increase thermal conductivity were verified by focusing on the behavior of solute atoms that solid solute in the aluminum metal matrix and obstruct thermal conduction in AC4B, an aluminum casting alloy used as a material for cylinder heads. This study is applicable to heat treatment type aluminum alloy in general, and can also be expanded to aluminum alloy parts with high demand for heat dissipation properties. In addition, the close relationship between thermal conductivity and electrical conductivity indicated the potential for a simple alternative method of measuring thermal conductivity.

1. Introduction

The heat treatment specs of aluminum alloy are known to influence thermal conduction, and Table 1 shows the heat treatment temper designation and thermal conductivity of aluminum wrought products⁽¹⁾. Thermal conductivity is influenced by the amount of solute atoms that are solid soluted (the amount of solid solution) in the aluminum metal matrix. Solute atoms in solid solution are consumed only by room temperature aging precipitation, and T4 treatment that has a high residual amount of solid solution exhibits the lowest thermal conductivity. In T6 treatment, the solute atoms are further consumed by the artificial aging treatment described hereinafter, so thermal conductivity is restored. In O materials, most of the solute atoms are consumed in coarse precipitates, resulting in the highest values. Similar tendencies are present in typical 2000 series alloy that is strengthened by Cu-based precipitates and in typical 6000 series alloy that is strengthened by Mg₂Si precipitates. These results indicate that thermal conductivity is influenced by the amount of solid solution of the residual solute atoms, regardless of the type of solute atom. On the other hand, the heat treatment conditions for aluminum alloy are mainly set for material strength, and in particular with regard to aluminum alloys for castings that are made of recycled materials, there is no known mention of the detailed effect on thermal

Table 1 Thermal conductivity of aluminum alloy with various temper designations

Alloy	Temper designation	Thermal conductivity (20°C) kW/(m·°C)
2014	T4	0.13
	T6	0.15
	O	0.19
2024	T3, T4	0.12
	T6, T81	0.15
	O	0.19
6061	T4	0.15
	T6	0.17
	O	0.18
6051	T4	0.16
	T6	0.17
	O	0.20

conductivity. Parts made of aluminum casting alloy are often used in power units that demand heat dissipation performance, such as internal combustion engines. Thermal load tends to increase as size reduction progresses, so it is thought that the thermal conduction of aluminum casting alloy will become a key functional element in considering future parts development.

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2. Objective

In order to know the influence of heat treatment on thermal conductivity, it is necessary to understand the solid solution and precipitation behavior of solute atoms in aluminum alloy. This study explores the approach of setting heat treatment conditions that increase the thermal conductivity of the AC4B alloy used in the cylinder heads of automobile, motorcycle, and outboard engines after achieving the demanded material properties. An approach is also proposed for control of thermal conductivity including other aluminum alloys.

3. Heat Treatment Conditions that Increase Thermal Conductivity

3.1. Solid Solution and Precipitation Behavior of Solute Atoms in Heat Treatment

First, an overview of the solid solution and precipitation of solute atoms that occur in heat treatment that elicits the material strength of aluminum alloy is explained. Figure 1 shows the typical pattern of T6 and T7⁽¹⁾ heat treatment performed on aluminum alloy. Solution treatment refers to holding at the solution treatment temperature to solid solute the solute atoms in the aluminum matrix and then rapidly

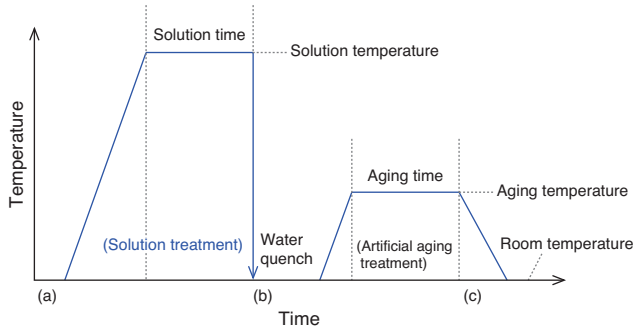


Fig. 1 Typical pattern of T6 and T7 heat treatments for aluminum alloy

cooling such as by water quench to achieve a solute atom supersaturation state. Artificial aging treatment (hereinafter, aging treatment) refers to holding at the aging treatment temperature to artificially precipitate the supersaturated solute atoms and obstruct the movement of dislocations of the aluminum metal matrix after that in order to suppress the deformation behavior of the metal and increase the material strength.

Figure 2 shows a schematic diagram of each state of the solute atoms in the aluminum metal matrix in process stages (a), (b), and (c) in Fig. 1. Figure 2(a) is a simplified model of a coarse precipitate formed in the initial stage due to the slow solidification rate in aluminum alloy casting raw materials. (b) is the state in which the solute atoms undergo solid solution into the aluminum matrix by solution treatment, and (c) is the state in which the solute atoms are formed as precipitates that contribute to enhancement of material strength by aging treatment.

The age hardening characteristic that occurs due to the movement and precipitation of solute atoms is known to be influenced not by the amount of solid solution of solute atoms that changes according to the solution holding time, but rather by the atomic vacancy density formed in the aluminum matrix based on the solution treatment temperature⁽²⁾. Equation (1) expresses the atomic vacancy density $C_v^{(3), (4)}$. Here, A is a constant (2 to 5), H_F is the atomic vacancy formation energy, k is Boltzmann's constant, and T is the absolute temperature.

$$C_v = A \cdot \exp[-H_F / (k \cdot T)] \quad (1)$$

As the atomic vacancy density is a function of temperature, it is determined by the holding temperature of the solution treatment, and those atomic vacancies are fixed in the aluminum matrix by water quench. Figure 3 shows a schematic diagram of how solute atoms move due to atomic vacancies. With regard to the movement of atoms, the energy barrier is lowered by passing through atomic vacancies, and thus the amount of aluminum atom and solute atom movement per unit time depends on the atomic vacancy density⁽⁵⁾.

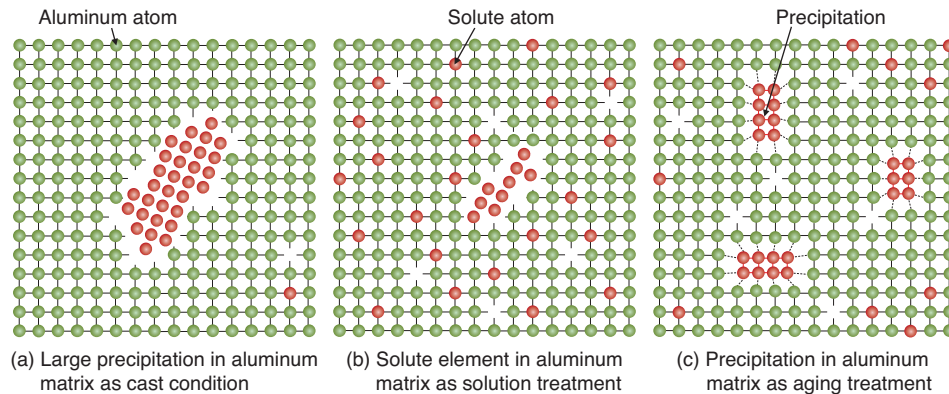


Fig. 2 Diagram of solid solution and precipitation in aluminum alloy

This section will verify that the age hardening characteristic depends only on the atomic vacancy density formed in the aluminum matrix based on the solution treatment temperature and not on the amount of solid solution of solute atoms determined by the solution holding time. Figure 4 shows the relationship between the solution holding time and the mechanical properties of the AC4CH alloy used in cast wheels. The solution treatment temperature was standardized at 540°C and the aging treatment condition was standardized at 140°C × 150 minutes. Precipitation hardening of the AC4CH alloy is due to Mg₂Si precipitates. As the solution holding time increases, solid solution of the solute atoms progresses and the amount of solid solution increases, but there is little effect on the mechanical properties even if the solution holding time is extended. This indicates that the age hardening characteristic is influenced by the atomic vacancy density, which is determined by the solution treatment temperature. Figure 5 shows the relationship between the solution holding time and elongation under the same heat treatment conditions as in Fig. 4. The reason why elongation increases together with the solution holding time is that spheroidization of eutectic silicon progresses and the crack propagation speed decreases. The objective of Sr addition in cast wheels is to increase the fineness of the eutectic silicon in order to stabilize the elongation characteristic and help achieve the demanded shock absorption characteristics. Sr addition helps to enhance production efficiency by shortening the solution holding time within the range that can help achieve the elongation value that is important in terms of the part requirement characteristics. As such, it is used as an effective method in materials for cast wheels.

3.2. Age Hardening Characteristic and Thermal Conductivity of AC4B Alloy

AC4B alloy for aluminum castings has a good balance of castability, mechanical properties, and high temperature characteristics, and is widely used as a material for cylinder heads. Table 2 shows the composition of the AC4B alloy test sample used in this study.

Figure 6 shows the age hardening characteristic due to aging treatment temperature of AC4B alloy after solution treatment at 500°C × 360 minutes. In order to remove the

Table 2 Chemical composition of AC4B alloy test sample

	(wt%)					
	Si	Cu	Mg	Fe	Zn	Mn
AC4B sample	8.2	2.7	0.34	0.76	0.67	0.24

influence of room temperature aging that occurs between solution treatment and aging treatment, all test pieces were stored at -20°C from immediately after solution treatment by water cooling until loading into the aging treatment furnace. In addition, a hot air circulation type drying furnace was used to keep a constant temperature in aging treatment. The main precipitation hardening of AC4B alloy is due to Cu-based precipitates.

With aging at 150°C to 180°C, the hardness is initially around HRB 60 due to metastable precipitates called the GP(1) zone and then increases due to the formation of an intermediate phase called the GP(2) zone⁽⁶⁾⁻⁽⁹⁾. With aging at 200°C to 235°C, hardening due to precipitation of the intermediate phase progresses from the initial stage, resulting in hardness of about HRB 75. Then, as the aging time increases, the intermediate phase coarsens and becomes the stable phase, and softening occurs.

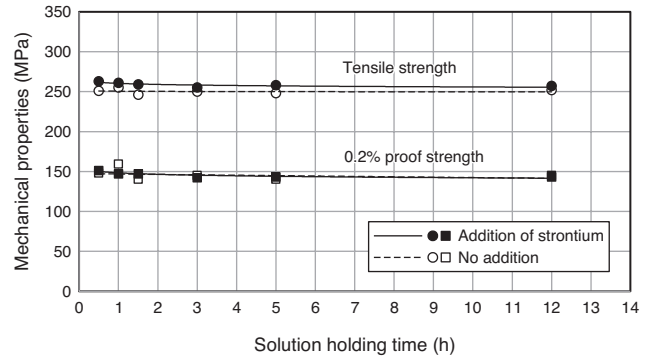


Fig. 4 Effect of solution temperature holding time on mechanical properties of AC4CH-T6

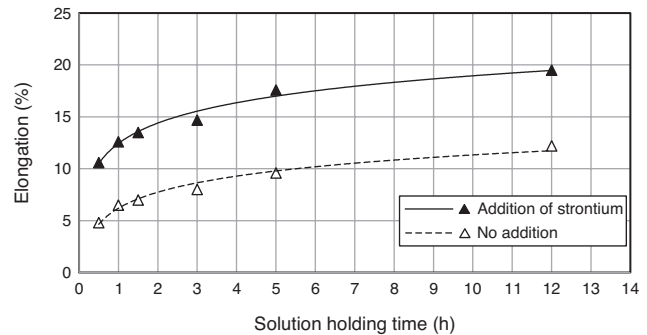


Fig. 5 Effect of solution temperature holding time on elongation of AC4CH-T6

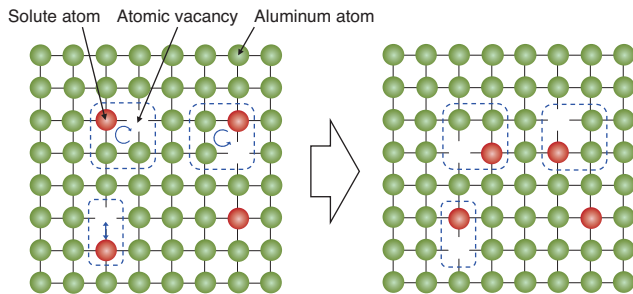


Fig. 3 Diagram of atomic vacancy and atomic diffusion

This section will verify how the thermal conductivity changes as solute atoms in solid solution are consumed by aging precipitation. Figure 7 shows the change in aging time and thermal conductivity at 160°C, 180°C, and 220°C, which exhibit a different age hardening characteristic, when solution treatment is performed under the same conditions as in Fig. 6. The thermal conductivity λ was calculated by measuring the thermal diffusivity α by the laser flash method and multiplying it by the density ρ at room temperature and the specific heat Cp measured by the DSC method. Equation (2) shows the thermal conductivity λ .

$$\lambda = \rho \cdot \alpha \cdot Cp \quad (2)$$

λ : Thermal conductivity [W/(m·K)]

ρ : Density [g/cm³]

α : Thermal diffusivity [m²/s]

Cp : Specific heat [J/(g·K)]

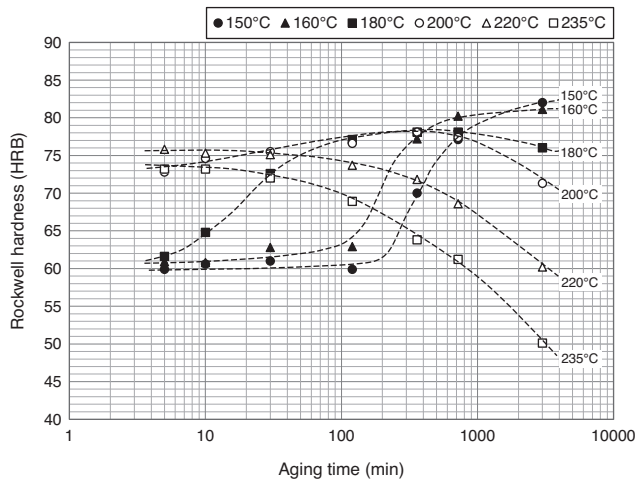


Fig. 6 Aging curve of AC4B alloy

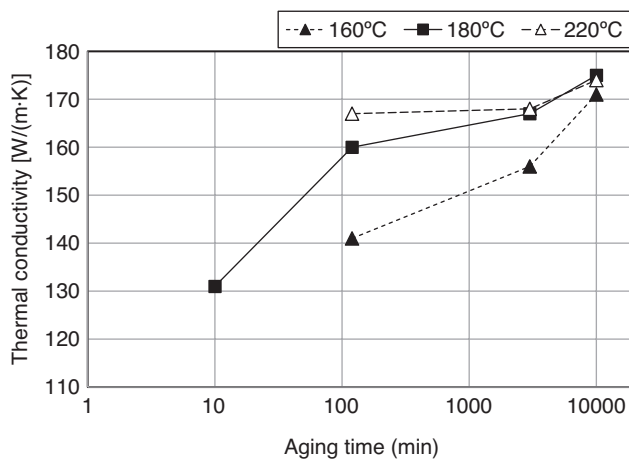


Fig. 7 Thermal conductivity with various aging treatments

It was confirmed that the solute atoms in solid solution are consumed by precipitation over time, and that thermal conductivity is enhanced accordingly. Precipitation tends to progress faster at higher aging temperatures, and thermal conductivity tends to be higher as more solute atoms are consumed. In addition, the thermal conductivity continues to increase even in the over aging area where hardness decreases, and thus it is presumed that the residual solute atoms obstruct thermal conduction.

3.3. Heat Treatment Condition Settings that Increase Thermal Conductivity of AC4B Alloy

This section will verify the approach to setting conditions that increase the thermal conductivity by reducing the residual amount of solid solution. Figure 8 shows the effect of solution holding time at 500°C on the age hardening characteristic of AC4B alloy at 200°C. Within the observed period, the age hardening characteristic at 200°C has an under aging area where the hardness increases and an over aging area where the hardness decreases, and this change was selected as an easy-to-understand condition. In the under aging area where the hardness increases, no difference in hardness was observed between the solution holding times of 10 minutes, 180 minutes, and 360 minutes. This lack of difference in hardness, which is closely correlated with yield strength, confirmed a similar situation to the results in Fig. 4 where solution holding time had no effect on the mechanical properties of AC4CH alloy. In the over aging area where the hardness decreases, a solution holding time of 10 minutes resulted in lower hardness compared with 180 minutes and 360 minutes. The reason for this is thought to be that the solute atoms needed for precipitation were depleted due to the small amount of solid solution.

Figure 9 shows the results of measuring the thermal conductivity of test pieces immediately after solution treatment held at 500°C for 10 minutes, 180 minutes, and 360

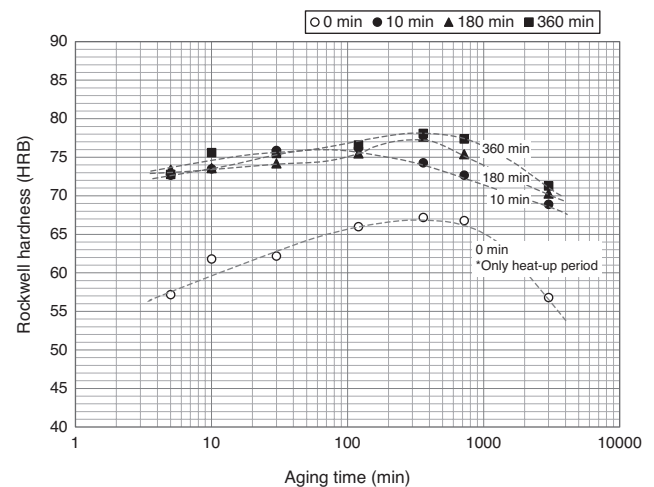


Fig. 8 200°C aging curve of AC4B alloy with various solution holding times

minutes, and of test pieces with equal hardness after addition of aging treatment at $200^{\circ}\text{C} \times 120$ minutes. All test pieces were stored at -20°C so that the amount of solid solution immediately after solution treatment did not decrease due to room temperature aging. In addition to storage at -20°C , the test pieces used to measure the state immediately after solution treatment were further treated to help prevent the advance of room temperature aging. This consisted of loading into a 100°C furnace for 10 minutes for exposure to higher than room temperature in order to help prevent consumption of solute atoms in solid solution by room temperature aging until the measurement of thermal conductivity.

The results show that immediately after solution treatment, the thermal conductivity decreases and the amount of solid solution of solute atoms increases in accordance with the increase in the solution holding time. After aging treatment at $200^{\circ}\text{C} \times 120$ minutes, the solute

atoms are consumed by the aging treatment and the thermal conductivity is restored in each case. However, even after aging treatment, longer solution holding times resulted in lower thermal conductivity, and thus it is assumed that the amount of solid solution of the residual solute atoms is higher at longer solution holding times. From this, it is thought that the solute atoms in solid solution in excess of the amount consumed by aging treatment remain even after aging treatment and become a factor obstructing thermal conduction.

This means that in order to increase thermal conductivity after achieving the demanded material properties, it is necessary to reduce the amount of solid solution of the residual solute atoms after aging treatment. The key to achieving this is to set solution treatment conditions that result in the amount of solid solution that is necessary and sufficient for aging precipitation. The necessary and sufficient amount of solid solution of solute atoms can be understood by performing verification with different solution holding times under aging conditions defined as shown in Fig. 8. This type of approach enables verification with a test piece cut from a part, and is useful in setting solution treatment conditions that increase thermal conductivity.

4. Examination

4.1. Application to Other Alloys

This section will verify that the approach of setting heat treatment conditions that increase thermal conductivity is also applicable to Al-Si-Mg-based alloy that is strengthened by precipitation of Mg_2Si in the same manner as AC4B alloy that undergoes precipitation hardening by Cu-based precipitates. Figure 10 compares the aging characteristic when solution treatment is performed at the standard temperatures of 535°C and 500°C in an Al-5%Si-0.3%Mg aluminum casting alloy, of which impact resistance is demanded like AC4CH. Age hardening results in higher

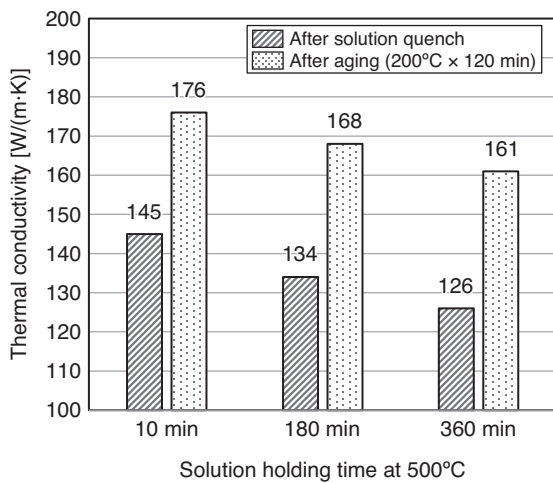


Fig. 9 Thermal conductivity with various solution holding times

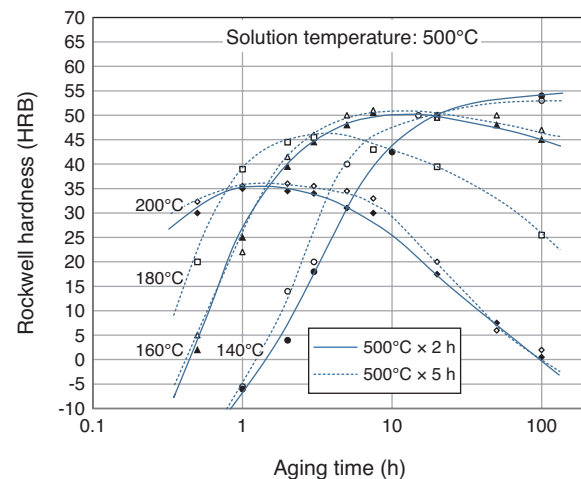
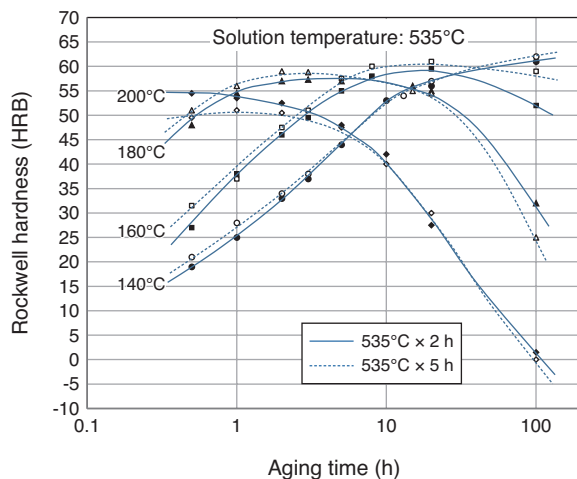


Fig. 10 Aging curve with solution temperatures of 535°C and 500°C of Al-5%Si-0.3%Mg alloy

hardness when solution treatment is performed at 535°C compared with 500°C, and there is no difference between solution holding times of 2 hours and 5 hours. This shows that like AC4B, the atomic vacancy density is the dominant factor for the age hardening characteristic. Therefore, the amount of solid solution of solute atoms that is necessary and sufficient for aging precipitation can be understood in the same manner as for AC4B alloy. The approach of changing the thermal conductivity by controlling the amount of solid solution of the residual solute atoms is applicable to heat treatment type aluminum alloy in general, regardless of the type of solute atom. Furthermore, application can also conceivably be expanded to aluminum alloy parts that demand heat dissipation properties, and conversely to parts that demand thermal insulation properties.

4.2. Issue for Practical Application

At present, measurement of thermal conductivity calls for dedicated equipment and skilled operators, and a simpler method is demanded to achieve thermal conductivity as a requirement characteristic. This section considers an alternative direction using electrical conductivity that is correlated with thermal conductivity. Figure 11 shows the correlation between thermal conductivity and electrical conductivity in various aluminum wrought product alloys⁽¹⁾.

It is known that in the thermal conduction of metals, the contribution of electrons is more dominant than thermal conduction due to lattice vibration (phonon), and a correlation appears because electrons are responsible for both electrical conduction and thermal conduction⁽¹⁰⁾.

Equation (3) shows the relationship between the electrical conductivity and thermal conductivity of metals, generally referred to as the Wiedemann–Franz rule. Here, λ is the thermal conductivity, σ is the electrical conductivity, L is the Lorentz number, and T is temperature.

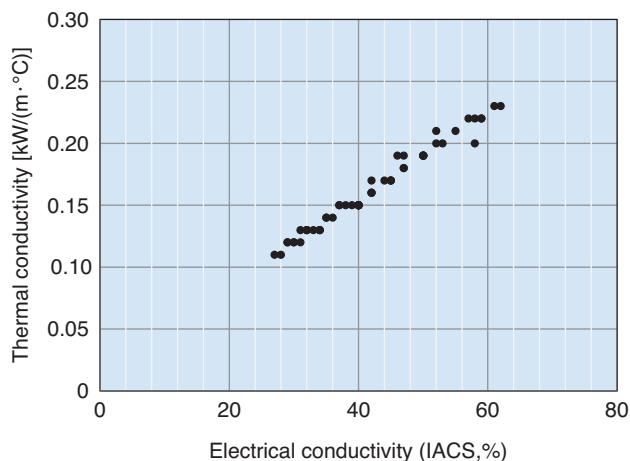


Fig. 11 Relation between thermal conductivity and electrical conductivity

$$\lambda / \sigma = L \cdot T \quad (3)$$

This indicates that if the temperature is the same, the ratio of thermal conductivity to electrical conductivity is nearly the same even for different types of metals. This presents future potential for replacing measurement of thermal conductivity with relatively simple measurement of electrical conductivity, and may be useful in both practical application of thermal conductivity as a requirement characteristic and in verification of more detailed changes in thermal conductivity.

Aluminum alloy has an established resource recycling environment, and many recycled materials including AC4B alloy are used and have facets as sustainable materials. The addition of thermal conductivity control technology is expected to enhance performance and expand the applications of existing products.

5. Conclusion

The following conclusions were obtained by verification and examination of thermal conductivity using the aluminum alloy AC4B.

- (1) In order to increase thermal conductivity after achieving the demanded material characteristics, it is necessary to reduce the amount of solid solution of the residual solute atoms after aging treatment. The key to achieving this is to set solution treatment conditions that result in the amount of solid solution that is necessary and sufficient for aging precipitation.
- (2) The approach of understanding the amount of solid solution that is necessary and sufficient for aging precipitation and changing the thermal conductivity by controlling the amount of solid solution of the residual solute atoms is applicable to heat treatment type aluminum alloy in general, regardless of the type of solute atom.
- (3) The measurement method is an issue for future practical application of thermal conductivity, but potential was shown for replacement by relatively simple measurement of electrical conductivity.

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Real-time Bolt Axial Force Fastening System Using Ultrasonic Waves in Mass Production Assembly Process

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ABSTRACT

In order to reduce variations in fastening force in mass production assembly processes, a real-time bolt axial force fastening system was developed to provide fastening force that is stable, whether the work is done by automated equipment or by humans. An ultrasonic wave method is used to measure axial force, with a gap between the bolt head and the probe for increased accuracy. Bolts used for measurement were bolts with specifications that allow for forming by existing manufacturing processes. The probe emits an ultrasonic beam that is propagated by means of a newly developed solid propagation medium and receives echoes separately from the head and bottom of the bolt. Operations on the two received echoes are carried out simultaneously so that measurements are stable even while fastening is underway, realizing real-time axial force measurement. As a result, measurement of axial force during fastening is realized without changing production takt time, bolt manufacturing costs, and other such existing conditions.

This technology is capable of bidirectional communication with nutrunners, the electric fastening equipment that has been widely adopted for mass production fastening processes. It can control fastening force to a preset axial force value, and it has successfully reduced axial force variations to one-tenth or less than what is experienced with existing torque methods of tightening.

1. Introduction

Demands from society for decarbonization in recent years have accelerated the electrification of the automobile. In electrified vehicles, the battery unit is ordinarily fastened to the floor with bolts. For this reason, there is a demand for being able to control the fastening axial force during manufacturing so that loosening and fatigue do not occur in the fastening portion due to bolt expansion from heat generated by the battery, stress in the axial direction from road load, or other such reasons. There are many other, similar fastening axial force control processes in automobile manufacturing, so the need for highly accurate axial force control is only ever increasing.

The current axial force measurement methods include the ultrasonic wave method for measuring stretching of the bolt shaft, the strain gauge method, the electromagnetic field method⁽¹⁾, and so on. Axial force measurement during the mass production assembly process is subject

to time constraints. For this reason, there is demand for tightening with sockets with the simultaneous use of measurement sensors. As shown in Table 1, however, the electromagnetic field method cannot readily be used simultaneously for structural reasons. The other methods cannot readily be used, either, for reasons related to layout constraints during measurement, the need for bolt machining and sensor attachment with glue, and the need for judgment of measurement results.

Due to these factors, the torque method has generally been used instead on the mass production line. The torque method, however, is affected by the coefficient of friction, the area of contact, and other such influences based on individual differences that are specific to the particular component. Therefore issues arose⁽²⁾ because axial force values are not stable and axial force variations of around $\pm 30\%$ normally occur. Consequently, designs are required to be capable of maintaining sufficient axial force even at lower limit values, but when the objects being fastened

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Table 1 Challenges of axial force measurement methods in mass production assembly

	Measurement during fastening	Layout constraints	Bolt machining	Human judgment
Ultrasonic wave method	Available (Good)	None (Good)	Surface only	Needed
Strain gauge method	Available (Good)	Wiring process (Not good)	Machining and gluing	Needed
Electromagnetic field method	Not available (Not good)	Sensor size (Not good)	Not needed (Good)	Needed

are large, the fact that the space and mass necessary for fastening increase becomes an issue.

The aim, therefore, is to realize real-time axial force fastening of bolts in the mass production process without complicating the process, without necessitating bolts to be processed for special measurement use, and without involving judgment of measurement results, as the strain gauge method and electromagnetic field method do. An ultrasonic wave method that is thought to offer the possibility of realizing axial force fastening without those complications and so on was developed. The development goal was not to affect the tightening socket layout, takt time, and bolt costs that are conditions of current mass production. In addition, it was made a necessary condition that the method would not change existing processes and that by integrating a nutrunner and an ultrasonic wave axial force meter, it would be made capable of simultaneously fastening a bolt and controlling the axial force.

2. Principles and Issues of Axial Force Measurement by Ultrasonic Wave

2.1. Principles of Axial Force Measurement by the Ultrasonic Wave Method

Axial force is the force of a bolt shaft that has been stretched by tightening trying to return to its original state. The axial force can be grasped by measuring the amount of stretching in terms of bolt length change. The amount of stretching and the change in propagation time of an ultrasonic wave passing through the bolt are in a proportional relationship, so measurement by ultrasonic wave uses the difference in propagation time before and after tightening in place of the amount of stretching.

Figure 1 shows the basic principle of axial force measurement by ultrasonic waves.

First the probe is put in close contact with the head of a no-load bolt, an ultrasonic beam is generated, and the propagation time (t_1) in microseconds (μs) until the bottom echo has been received is recorded. Measurement is also made after tightening, and when that propagation time (t_2 in μs) is acquired, the difference in propagation time from before tightening is calculated. The propagation time can

be converted into length of (x) mm by multiplying it by the material-specific sound velocity. By multiplying this value with the spring constant (k) in N/mm of the bolt, the axial force value (F) in kN is calculated.

The calculation of the axial force value is expressed as in Eq. (1).

$$F = k (x_2 - x_1) \quad (1)$$

2.2. Method of Setting the Measurement Reference Point

The reference point for measurement is acquired by setting a gate for echoes from the several wave lengths acquired. Gate refers to the time position and section of waves that are monitored, together with their height level. In order to compensate for attenuation due to the time direction movement of the echo that accompanies tightening of the bolt, the change in measured length, and other such factors, the position that is set is ordinarily placed in a broad section with a width of about three wave lengths from the first wave, and lower than the peak position of the waveform.

For setting the measurement reference point, the zero cross method that involves less influence from waveform change is commonly used⁽³⁾. The zero cross method is a method that sets the reference point at the zero-cross point, which is where a wavelength of height exceeding the gate position first intersects with the zero baseline. Figure 2 shows the method of setting the reference point.

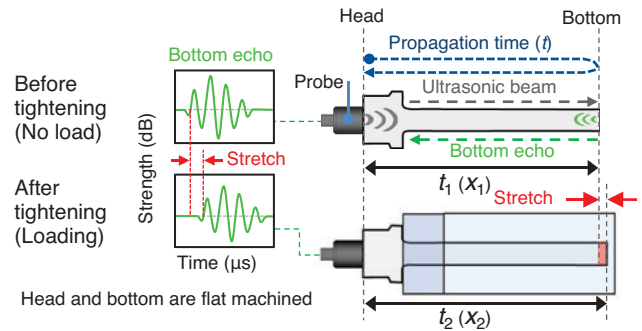


Fig. 1 Principle of axial force measurement by ultrasonic waves

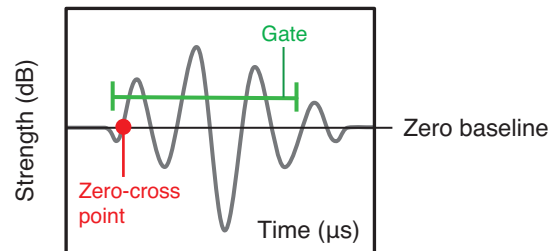


Fig. 2 Reference point setting method for echo

2.3. Issues of the Ultrasonic Wave Method

Measurement by ultrasonic wave is carried out with the probe placed closely against the bolt head surface at a constant pressure. However, the echo from the head cannot be distinguished when the distance from the head is so small, so measurement is not of the pure bolt length, but rather of the distance (T-B1) between the transducer (T) built into the probe and the bottom echo (B1).

Figure 3 shows an overview of the probe structure and bolt contact.

Piezoelectric ceramic (PZT) is ordinarily used for the transducer, which is covered by a protective plate layer⁽⁴⁾,⁽⁵⁾. Ultrasonic waves emitted by the transducer pass through the protective plate and the flexible layer of propagation medium and propagated to the bolt. At this time, if the applied load of the probe and its mounting position are changed, the thickness of the flexible layer will change and the measurement distance will be affected.

A high degree of shape accuracy in terms of bolt flatness, squareness, surface roughness, and so on is sought as a way to address this⁽⁶⁾. For that reason, it was necessary for the bolts used for ultrasonic wave measurement to be machined by high-precision cutting.

In addition, if air is present between the probe and the measurement surface, then the sudden change in the acoustical impedance characteristics will cause attenuation of the ultrasonic wave, resulting in measurement malfunction⁽⁷⁾. In order for there not to be a layer of air, a flexible propagation medium is necessary. A liquid propagation medium that can fill the space all the way to a minute layer of air is therefore used. However, a liquid coating process cannot readily be added to the existing mass production assembly process because it would impose additional takt time and costs.

Furthermore, even when the probe position and bolt shape accuracy have been secured, the application of axial force may result in stress inside the bolt, and the influence of distortion may change the acoustical characteristics⁽⁸⁾ so that echo output and time position are no longer stable. Figure 4 shows a typical example of such change. As this indicates, when tightening reduces the echo output from the first wave, that wave misses the gate so that the zero-cross point is moved to the second wave. This resulted in the issue of the measurement distance ending up being displaced

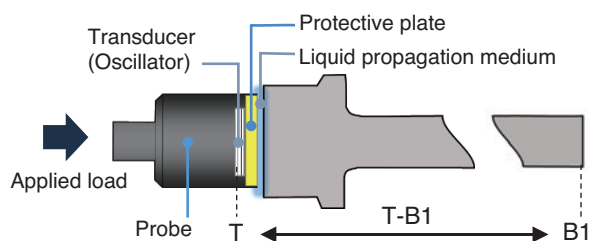


Fig. 3 Overview of probe structure and bolt contact

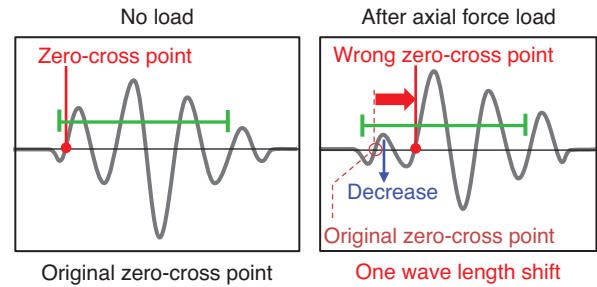


Fig. 4 Effect of changes in echo output on measurements

by one wave length. When the measurement reference is displaced in this way, it can lead to mismeasurement. For this reason, it was necessary for the person performing measurement to make corrections by checking and adjusting the gate position, and so on.

3. Overview of Real-time Axial Force Fastening System Using Ultrasonic Wave

In order to reduce variations in fastening force during the mass production assembly process, a real-time axial force fastening system that operates by ultrasonic waves was developed. Figure 5 shows the basic system configuration.

An ultrasonic wave axial force meter was integrated with the nutrunner used for tightening in order to incorporate coordinated control by intercommunication.

The probe for axial force measurement is held inside the interchangeable tightening socket at the tip of the nutrunner, where it is retained by a spring. When the probe touches the bolt head, it is in close contact with it and instantly measures the bolt length. The probe is electrically connected with the ultrasonic wave axial force meter through a slip ring, and it sends the nutrunner a signal to begin fastening.

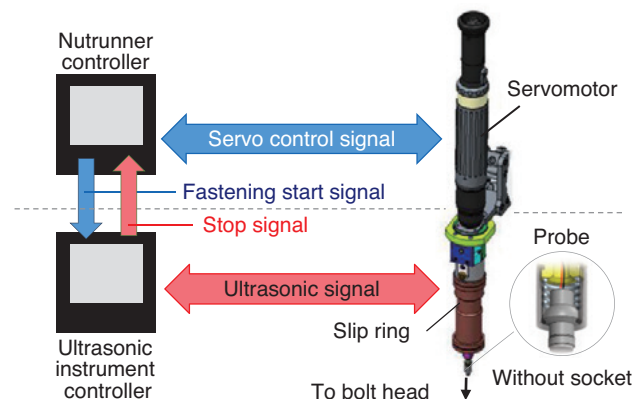


Fig. 5 Basic system configuration

The bolt length is measured in real-time, even while fastening is underway, and that length is converted in an axial force value. When the specified axial force is reached, the fastening force is controlled and stopped.

A method of measurement that is not influenced by the probe position or bolt shape accuracy was developed. A gap was set between the probe and the bolt so that, in addition to the bolt bottom echo, the new head surface echo (S) could also be measured.

In this way, a measurement method was devised that would be able to obtain the pure bolt length regardless of the probe position.

The issue of zero-cross point shift was also addressed by a program that continues to track the point even when the waveform changes.

For the propagation medium, the liquid was replaced with a flexible elastomer material. This made repeated reuse possible and made the liquid application process unnecessary. In addition, by putting this in an integrated structure with a high hardness resin material, a non-deforming portion was added and the state when mounted against the bolt was stabilized.

4. New Measurement Method and Technology Applied

4.1. Measurement Method for Application to Mass Production Process

4.1.1. Effectiveness of measurement method with gap set

In the mass production fastening process, there are factors such as automated equipment and differences in human skill that can cause the probe position to vary. As a measurement method that would not be influenced by these factors, the S-B1 measurement method that recesses a part of the bolt head and simultaneously measures the head and bottom echoes was developed⁽⁹⁾. Figure 6 shows the gap

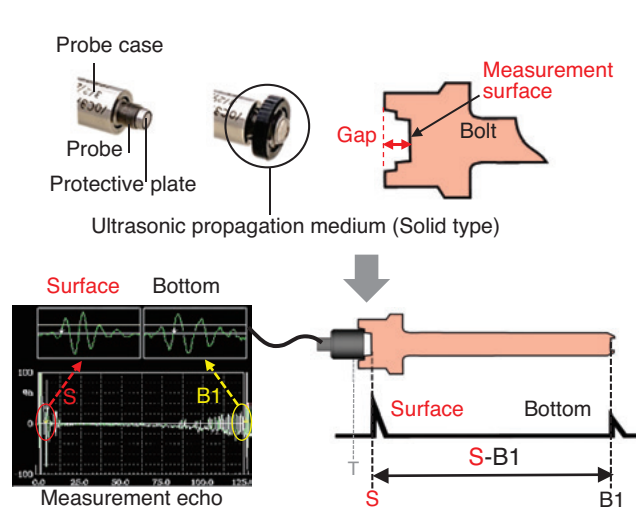


Fig. 6 Gap structure and measurement method

structure and measurement method.

By this means, it became possible to grasp the relative time difference in echoes from both ends of a bolt in real-time, and to measure the pure bolt length regardless of the probe position.

As a result, it became possible to determine the change in bolt length accurately without being affected by work skill levels and so on. The issues with probe position and component accuracy were also addressed. Moreover, since existing methods involved placing the probe vibrating surface in contact with metal bolts, this sometimes led to cracking of the transducer. As a result of adopting the S-B1 method, it became possible to help avoid direct contact with rigid objects.

4.1.2. Measurement reference point anti-displacement function

An auto-tracking function was developed that automatically tracks waveform changes when measuring axial force. With conventional measurement methods, the operator would visually inspect the waveform. If a change in the zero-cross point was seen, the operator would make manual corrections by adjusting the waveform gain or the gate position, and so on. The same function is already in use with ultrasonic wave flaw detection, where the method used was to cause the gate position to be tracked when the echo changed.

With axial force measurement, however, the amount of change in the bolt head differs from that in the shaft. A new two-gate tracking function was therefore developed to track the gate positions according to their respective amounts of change⁽¹⁰⁾.

Figure 7 shows the two-gate tracking system.

This function synchronizes with the ultrasonic wave pulses that are emitted at a high frequency of about 1 kHz and acquires the individual propagation time for each gate.

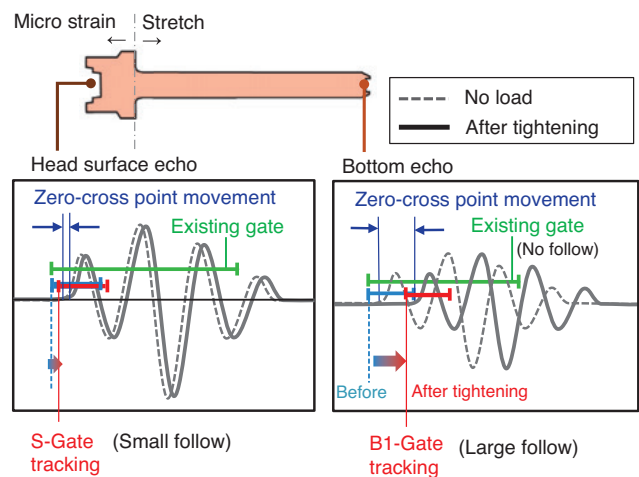


Fig. 7 Operational schematic diagram of newly developed two-gate tracking method

The difference from the previously acquired propagation time is calculated for each gate and the gate position is corrected. As a result, the gate position is also tracked with respect to the amount of change in the echo time position that occurs with bolt fastening. The gate can therefore be configured to be as narrow as the one wave length width that is necessary to set the zero-cross point. Consequently, the occurrence of mismeasurement factors is inhibited and the work of checking and correcting the measurement reference point was made unnecessary.

4.1.3. Fastening state stability judging function

When implementing fastening control by means of axial force values, the possibility for carrying out axial force fastening regardless of the operator's skill becomes necessary. Two-gate tracking and other such functions help reduce the burden on the operator, but there is a need for a function that can automatically detect irregularities in tightening and measurement and judge the fastening state.

A malfunction-detecting function that uses the frequency characteristics of acquired echoes was developed⁽¹¹⁾ as a method for judging the fastening state. This function is focused on changes that occur in the waveform shape as detected from the tilt of the probe, transducer wear, foreign substances, bolt irregularities, and other changes in peripheral conditions. A fast Fourier transform (FFT) was applied in advance to a malfunction waveform and the three items of center frequency, peak frequency, and fractional bandwidth⁽¹²⁾ were entered in a database. Then it automatically detects the presence or absence of malfunction by comparison with the measured waveform during tightening.

Figure 8 shows examples of FFT analysis for normal and malfunction states.

Malfunction detection is carried out from the time when the probe comes in contact with the bolt to when tightening is completed. When a malfunction is judged to have occurred, the system is set to control the nutrunner and stop it.

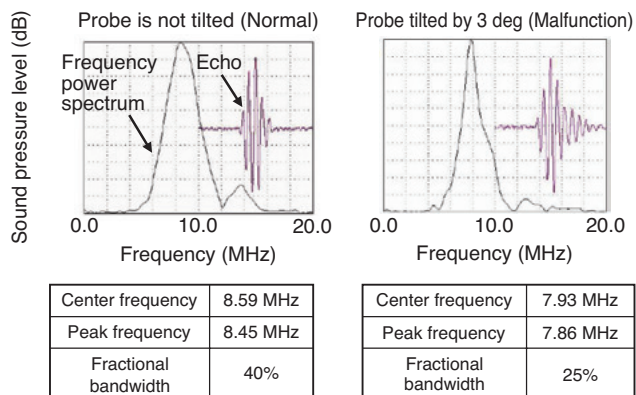


Fig. 8 Examples of normal and malfunction FFT analysis

4.2. Solid Ultrasonic Wave Propagation Medium for Application to Mass Production Process

In order not to enlarge the fastening work process, solid propagation medium was developed to use in place of a liquid. As shown by its shape in Fig. 9, this medium has a hybrid structure with an ultrasonic wave propagating part that uses a relatively soft elastomer material with a hardness of about 15⁽¹³⁾ and a fixed part that uses the high hardness resin material polypropylene (PP).

Since a characteristic of the elastomer material is that its shape can readily be changed, it is suited to filling the space between the probe and the bolt head. However, in prior checks using the elastomer on its own, after it had been repeatedly compressed by more than 50% some tens of times, cracking and plastic deformation occurred so there was a possibility that its functionality as a propagation medium could be impaired within a short time. Because it is a soft material, it could not readily be made to maintain a fixed shape, so the probe position ended up becoming unstable with respect to the bolt, and there were issues with the method of fixing the elastomer material itself in place. The issues were therefore addressed by making it a two-color molded part together with the PP material.

4.2.1. Method of fixing medium in place and effectiveness of probe position stabilization

As shown by the structure in Fig. 10, a screw-in style was adopted for the method of fixing in place. The PP part was shaped to an appropriate length as a female screw. By screwing it onto the probe tip, which was shaped as a male screw, the elastomer material and the vibrating surface are fixed in a position of contact. The PP part of the propagation

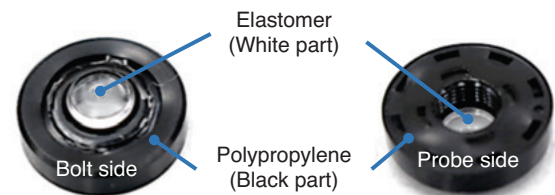


Fig. 9 Solid type ultrasonic propagation medium

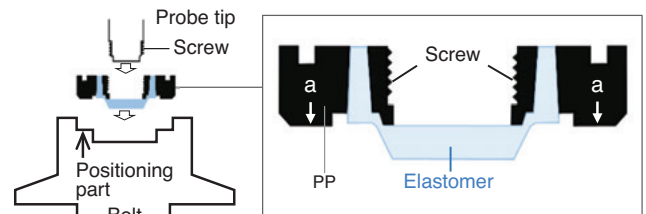


Fig. 10 Cross-section and peripheral layout of ultrasonic propagation medium

medium, which is fixed in place, fits together with the positioning part on the bolt side, which is in the first level of the recessed area, securing the stability of the probe position. The elastomer material part comes into contact with the measurement surface, which is in the second level of the recessed area, where it propagates ultrasonic waves. Making it detachable by means of the screw shape also gave consideration to its replaceability.

4.2.2. Durability of elastomer material

To secure the durability of the elastomer, the compression ratio of the elastomer is kept to 50% or less to control the amount of the material that projects from the bolt contact surface of PP material (surface a in Fig. 10). To confirm durability, it was tested by repeatedly compressing it against a bolt shape. The result was that a portion was observed to whiten after 150,000 compressions, but it retained normal measurement function in terms of its shape and propagation characteristics. Supposing a mass production process that involved 1,000 iterations of tightening work in one day, this confirms durability corresponding to a total of 150 days of tightening work. Figure 11 shows the state of the solid propagation medium after testing.

4.3. Anti-lifting Probe Structure for Application in Mass Production Process

During the fastening process, it is conceivable that the fastening equipment may become tilted due to work circumstances or other such external factors. When that happens, if a part of the probe lifts away from the bolt, the close contact will be disrupted and measurement malfunction could occur. As a measure against this, a spring is used in the part where the probe and the fastening

Number of samples: 48

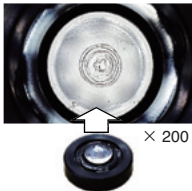
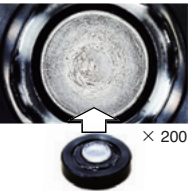
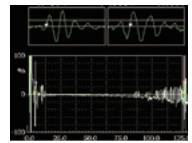
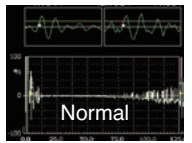
Number of compressions	0	150,000
Elastomer state	 × 200	 × 200
Change in outer diameter	(Standard ± 0.05)	-0.01 to +0.03
Change in thickness (mm)	(Standard ± 0.05)	-0.02 to +0.02
Measured echo		

Fig. 11 Results of repeated compression durability test

equipment are connected in a floating holding structure. This structure can keep the probe from being influenced by tilting of the equipment. As can be seen in Fig. 12, however, which shows a structure based on a general cylindrical probe shape, when the floating function was added using a general purpose probe, the structure ended up having a fulcrum at a location that is removed from the end of the bolt. Because of this, the range of probe movement from the bolt measurement surface was narrowed by about 1.5 deg, and this limited the response to tilting due to external factors.

In order to deal with large amounts of tilting, therefore, the probe structure was reviewed and another floating function was added at a location close to the bolt end.

The part that is in contact with the added spring was made spherical so as to secure an additional 5 deg for the range of movement in all directions. This secures flexible close contact by the probe against bumping or rattling of the fastening equipment or tilting resulting from human operation^{(14),(15)}.

Figure 13 shows the new floating holding structure.

4.4. Axial Force Measurement Bolt Applicable in Mass Production

In this development, the bolt head needed to have two functionalities that serve in measuring axial force and stabilizing the probe position. To support these, a mass production bolt was used as a base and a two-level recess was added to it.

With the layout of a general purpose probe, however,

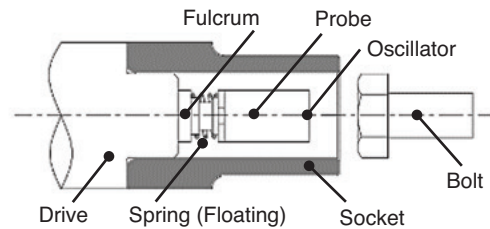


Fig. 12 General structure of probe in tool

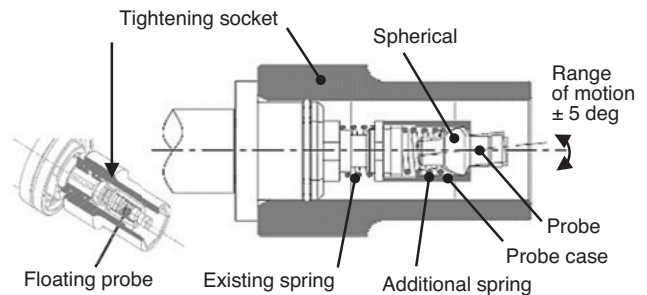


Fig. 13 New floating holding structure for probe

as shown by the shape in Fig. 14, a deep counterbored shape in the axial direction of the bolt becomes necessary. Therefore upset forging limitations^{(16), (17)} influence it during heading and the molding shape cannot readily be achieved. In the automotive components field, boron steel is commonly used for bolts of strength class 10.9 or lower^{(17), (18)}. Therefore the bolt head recess was shaped to maintain measurement accuracy even with boron steel⁽¹⁹⁾.

4.4.1. Optimization of molded shape

With deep counterbored shape molding, the flow of material cannot readily be tracked. As indicated by the comparison of molding analysis results shown in Fig. 15, areas appear where the mold has not contacted the steel material. This and other such issues with molding were found.

This was addressed by verifying the optimal shape using heading analysis (DEFORM ver. 11.1 from Yamanaka Eng Co., Ltd.) in a parametric study by bolt head shape. Based on the results, enlarging the recess diameter and making the measurement surface shallower produced a shape with uniform pressure on the working surface on a par with mass production bolts. This shape yielded the prospect of securing moldability without changing the existing mass production process or materials. The change in bolt head shape also necessitated a change in the shape of the probe that faces it. With this measurement method, however, it is the propagation medium, not the probe, that serves as the surface coming in contact with the bolt. The propagation medium is formed from resin materials and is made

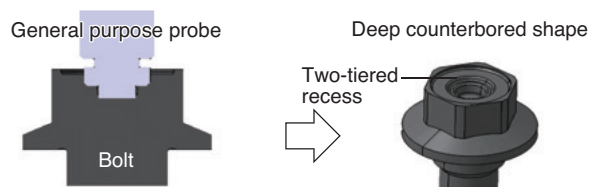


Fig. 14 Deep counterbored shape of bolt head

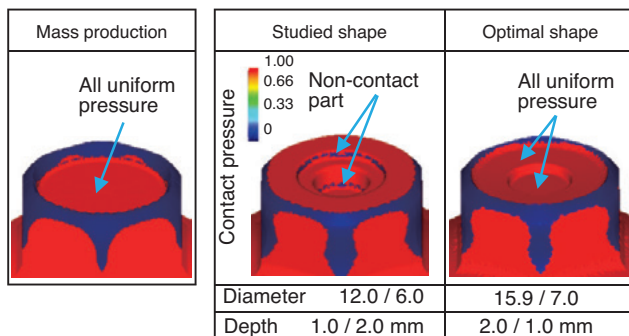


Fig. 15 Comparison of molding analysis

detachable so that it can change readily to conform to the bolt head shape.

4.4.2. Molding verification in the bolt mass production process

The mold was fabricated based on the molding analysis results and molding verification was carried out on the mass production line (using 1,000 samples). Figure 16 shows the tolerance process capabilities for the set dimensions. As this indicates, the recess diameter, gap depth, and parallelism between measurement surfaces that are important to ultrasonic wave axial force measurement exceed the general process capability index of 1.33 by a large amount⁽²⁰⁾, and moldability equal to the molding analysis was achieved.

The dimensional accuracy required for bolts in ultrasonic wave axial force measurement was secured by means of these results. It became possible to manufacture the bolts by the same molding process used for existing mass production molded bolts without having to add further processes.

4.4.3. Fatigue strength characteristics

The application of axial force to the bolt causes tension from the screw portion and repulsive force from the flange seating surface to intersect so that a concentration of stress occurs below the neck where the flange terminates. Figure 17 shows the sectional shape of the developed bolt. As this indicates, the developed bolt has a two-level recess shape in the bolt head, and the distance from the recess bottom to the bottom surface of the flange is short by comparison with the

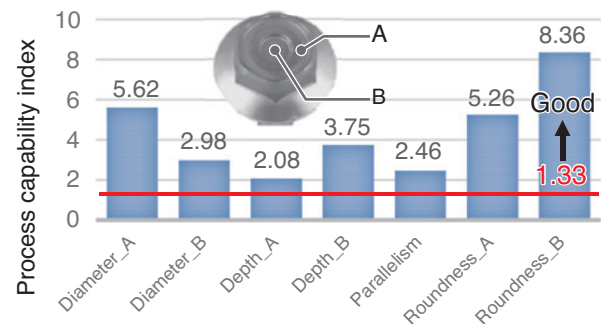


Fig. 16 Tolerance process capability index

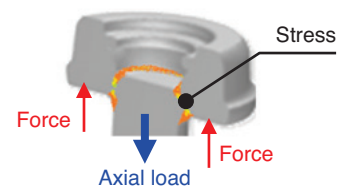


Fig. 17 Stress concentration by bolt fastening

ordinary bolt shape. This makes stress tend to concentrate. For this reason, it was necessary to help assure the fatigue strength in order to secure adequate performance against fracturing from long-term use.

Therefore the tensile fatigue test prescribed in JIS B 1081⁽²¹⁾ was carried out as comparative verification testing of the fatigue strength and fracture locations in the developed bolt and the mass production-based bolt. Figure 18 shows the results.

The test results show that under conditions of average stress at 70% of standard yield load (in the case of bolts, axial force)⁽²²⁾ at 0.2% yield strength, fatigue strength results equal to the mass production-based bolts were obtained. In addition, the fracture sites all occurred in the screw portion, and it was confirmed that adding the shaped recess to the bolt head did not have any influence on fatigue strength.

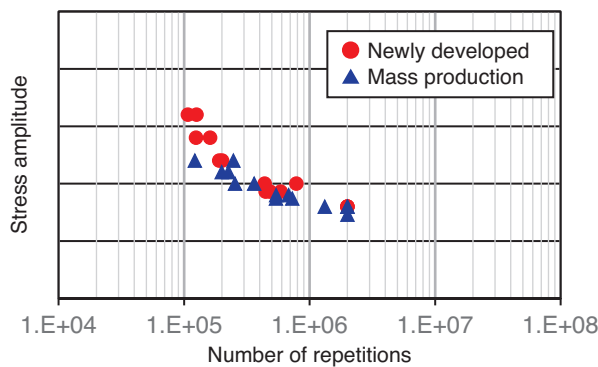


Fig. 18 Fatigue strength comparison test results

5. Fastening Verification Results

Verification was conducted to confirm the tightening accuracy of the real-time bolt axial force fastening system. For verification, six noise factors that are considered possible influences on ultrasonic wave axial force measurement were isolated and tests based on quality engineering methods⁽²³⁾ were carried out. As a result, sensitivity characteristics were obtained for the three factors of bolt effective diameter, grip length, and female screw length. Grip length is the length from the bolt neck under the flange part to the position where the female screw starts to engage. The female screw length is the actual length of the part where the female screw and male screw are engaged. These malfunction factors occur because of dimensional variations between individual products.

The M8 size bolt, which is used in mass production engines and has high accuracy requirements, was taken as the base for confirming tightening accuracy. Verification bolts were fabricated to reflect the upper, middle, and lower

limits in the drawing with respect to the three malfunction factors.

Verification bolts were used for confirmation and measurements were made five times ($n=5$) each for each factor alone and for their combinations. From the 1,000 measurement bolts manufactured in the mass production process, 30 bolts were added, making a total of 130 times ($n=130$) that tightening by axial force control was confirmed.

A tightening test jig with calibrated load cells built in, with the structure shown in Fig. 19, was used to carry out confirmation of the accuracy of ultrasonic wave axial force measurement. The test jig allowed movement and exchange of the female screw part, so the grip length and female screw length can be adjusted. The measurement accuracy was sought in this way from the difference between the load cell measurement value and the ultrasonic wave system measurement value.

The outcome was the favorable results obtained with a variation width of 0.96 kN ($\pm 3\sigma$) for the M8 bolt target tightening axial force value of 22.5 kN.

Figure 20 shows the fastening accuracy verification results for the real-time bolt axial force fastening system.

This is a variation of $\pm 2.1\%$ with respect to the axial force value taken as the target. Compared to the $\pm 30\%$ ⁽²⁾ when tightening with the torque method, this is a reduction to one-tenth or less.

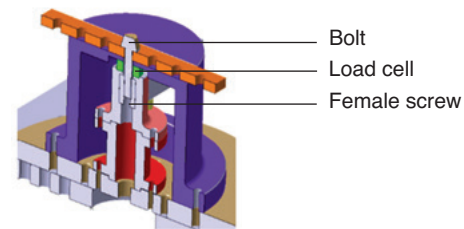


Fig. 19 Structure of test jig

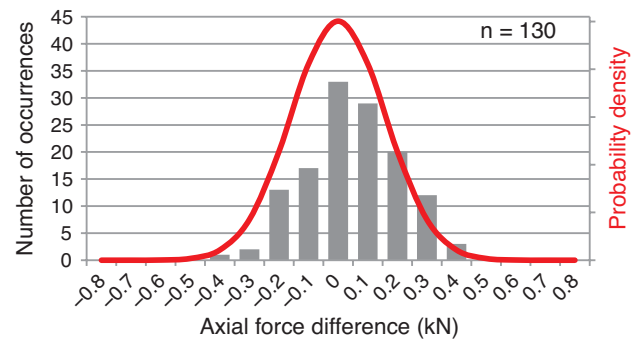


Fig. 20 Accuracy verification results for bolt axial force with this system

6. Conclusion

A real-time bolt axial force fastening system that is suited to axial force measurement under mass production assembly conditions was developed.

- (1) A two-gate measurement method with a gap opened in the bolt head was developed.
- (2) It became possible to obtain stable measurement results by means of two-gate tracking and a malfunction judging function.
- (3) The method was made adaptable to use in the mass production environment by developing a solid propagation medium using elastomer material in place of liquid together with a probe holding structure to deal with tilting of the measurement equipment.
- (4) Specification were created for bolts to use in measurement that can be produced without changing existing manufacturing methods, and increases in manufacturing costs were kept under control.
- (5) Axial force variations during fastening were successfully reduced to one-tenth or less by comparison with the torque method.

This technology addresses issues in the production processes for a wide range of industrial products and is thought to be a potentially important technology for increasing product strengths.

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Proposal of Evaluation Metric for Machine Learning Model for Battery Voltage Estimation

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ABSTRACT

In order to evaluate a machine learning model that estimates the voltage of a lithium-ion battery, we built a new accuracy evaluation metric based on the Arrhenius law, and tested it to see if it could be used to judge the relative merits of machine learning models. Two types of machine learning model were selected. One was a type that performed discrete estimates in regions where data are not available, while the other was capable of performing continuous estimation. Then, discrete temperature data based on floating car data collected from electric vehicles were generated, and the models were trained and evaluated. The results confirmed that the commonly used evaluation metric for evaluating deviation from test data showed no clear differences in evaluation results between the two model types. On the other hand, the authors' new evaluation metric based on the Arrhenius law showed clearer differences in the evaluations of the two models. Implementing this metric made it possible to evaluate a machine learning model even with limited collected data, thereby advancing the practical application of battery voltage estimation technology using machine learning models.

1. Introduction

Aiming to achieve carbon neutrality by 2050, Honda is developing battery electric vehicles (hereinafter, BEV) and fuel cell vehicles. Lithium-ion batteries (hereinafter, batteries) are widely used for energy storage in BEV⁽¹⁾. It is known that normally, the overpotential of a battery (the difference between closed and open circuit voltages) changes according to usage environment factors, such as temperature and energy demand from the vehicle, and the amount of energy that can be output varies^{(2),(3)}. Being able to estimate with high precision the overpotential of a battery under given conditions is believed to enable highly accurate estimates of the BEV cruising range in all environments. This in turn will reduce the risk of power depletion and helps eliminate customer anxiety about running out of power.

In recent years, it has become possible to collect large volumes of real-world data (floating car data) from running vehicles, and research is being actively pursued on battery voltage estimation technology that utilizes battery big data and machine learning⁽⁴⁾⁻⁽⁶⁾. As an example of prior research, one study reported research in which an algorithm was created for estimating voltages using deep learning, based on battery time-series data collected from electric buses⁽⁴⁾.

Shuangqi Li et al. tested voltage estimation accuracy with test data created based on the time-series data. The result was that the voltage could be estimated with a mean absolute percentage error (MAPE) of 2.42%. Another example of prior research is a study in which a battery charge/discharge cycle test was performed using a charge/discharge test device, and an algorithm was created for estimating battery voltages and temperatures with machine learning based on the collected data⁽⁵⁾. Manh-Kien Tran et al. used 30% of the data as test data and tested the accuracy. They reported as a result that the decision tree model was able to estimate voltage and temperature with a 0.99 coefficient of determination. The authors are focusing on machine learning as a technology that can reproduce with high accuracy the non-linear voltage behavior of batteries affected by multiple factors.

However, to actually apply this technology, it is necessary to fully determine how batteries are used in the market. For example, battery usage conditions differ depending on power unit types, such as BEV, hybrids, and plug-in hybrids, and vehicle properties, such as those of city commuters or long-distance vehicles. An inability to acquire sufficient training data is also a consideration. Due to such differences in battery usage conditions, it is believed that estimation accuracy will differ depending on

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the type of machine learning algorithm⁽⁷⁾. For this purpose, it is necessary to select an appropriate machine learning method corresponding to the battery usage data, which differ depending on the vehicle characteristics and market.

In this study, a method is tried that uses electrochemical knowledge for assessing the machine learning models. The paper proposes a method for assessing battery voltage estimation machine learning models, using the Arrhenius law, a commonly known law about chemical reactions.

2. Issues and Approach

2.1. Data Related Issues

Unlike physical models that calculate estimated values deductively, machine learning modelling learns data tendencies inductively based on collected data, and then calculates estimated values. Therefore, estimation in the absence of collected data may become less accurate.

As one example, Fig. 1 shows the results when comparing how machine learning models perform estimates in regions where data are not available. The following four types of machine learning models are being compared. The explanatory variable is x and the target variable is y .

- Random Forest Regressor (RF)
- K-Nearest Neighbors Regressor (KNN)
- Gaussian Process Regressor -RBF kernel (GP)
- Support Vector Regressor -RBF kernel (SVR)

Here, the RF and KNN models perform discrete estimates in regions where data are not available, while the GP and SVR models are capable of performing continuous estimation.

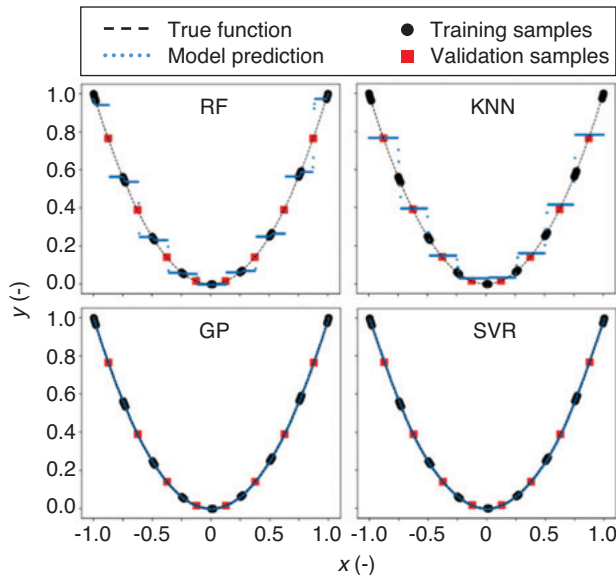


Fig. 1 Comparison of estimation results of machine learning models when data are given discretely

The dashed line in Fig. 1 shows the true trend $y=x^2$ while the dotted line shows the machine learning model's estimated values. The circles are the training data; the squares show the validation data for hyperparameter tuning. Both are discretely sampled from the true trend. The results showed that for both machine learning models, when data were available, estimated values were close to the true trend. On the other hand, in conditions where learning and validation data were unavailable, it was confirmed that estimates produced by the RF and KNN models deviated from the true trend. In the RF model, node branches along the decision tree are generated with reference to the training data to learn the data tendency. Therefore, it is a property of the model that when given discrete training data, the estimated values are discrete. The KNN model is an algorithm that calculates estimated values based on neighboring data within the training data. Therefore, like RF, it is a property of the model that when given discrete training data, the estimated values are discrete. It follows that in cases where the true trend changes continuously, the RF and KNN models tend to deviate from the true trend where data are unavailable. With the GP and SVR models, it was possible to confirm that even within ranges where validation data are unavailable, estimations do not deviate from the true trend. It is believed that this is because the property of GP and SVR models that estimates values continuously is effective in learning continuous true trends. It follows from this result that, in order to test whether a machine learning model can learn a true trend, validation with discrete data alone is insufficient, and comprehensive validation after continuously changing the explanatory variables is required.

2.2. Approach

As described in the foregoing section, in order to apply battery voltage estimation technology using machine learning models, it is necessary to address the issue of continuously and comprehensively assessing the machine learning model.

As an answer to this issue, one possible approach is to comprehensively collect floating car data in all conditions and perform comprehensive machine learning model validation. However, the conditions that can be obtained from the floating car data depend greatly on the vehicle usage environment. For example, temperature data depends on the climate in which the vehicle is driven, and there is no guarantee that continuous and comprehensive data can be obtained encompassing low to high temperatures. Therefore, it is possible that, to collect the necessary and sufficient data, the data would need to be gathered from a large number of vehicles over a long period of time. However, from a practical point of view this is not feasible, so another validation approach is needed.

To address the above issue, in this paper the authors propose a new evaluation metric drawing on electrochemical knowledge. With this evaluation metric,

continuous and comprehensive data are generated virtually and input into the machine learning model, and the response to the input data of the outputted values is evaluated. When the input data are generated virtually, there are no true values corresponding to the model's output values, so it is not readily possible to quantify the deviation between the output values and true values. However, the values output in response to changes in the input data can be expressed as a trend using an electrochemical theoretical formula. In the proposed approach, a quantitative evaluation metric is calculated by comparing the output value response of the model to changes in the input data and the theoretical formula.

In this study, discrete temperature data was generated from collected floating car data, then four types of machine learning models (RF, KNN, GP, and SVR) were trained and evaluated. Then, tests were conducted to see if it was possible to determine differences between RF and KNN models that perform discrete estimations and GP and SVR that can perform continuous estimations, when the training data are provided discretely.

3. Validation Steps

Figure 2 summarizes the validation steps in this study. The overall analysis consists of two steps, namely, Step 1: Model Training and Step 2: Model Evaluation. In Step 1, the data required for training the machine learning models are generated based on battery floating car data collected

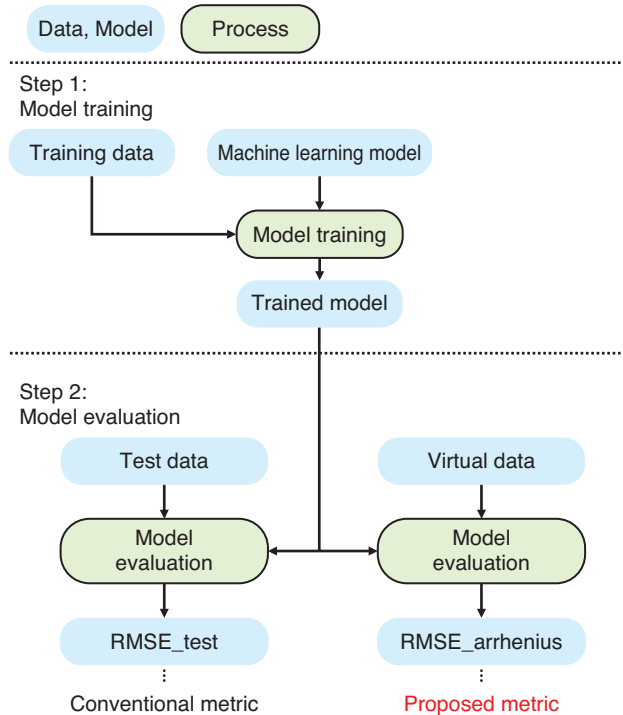


Fig. 2 Flowchart of entire evaluation in this study

from vehicles. Then, the four machine learning models (RF, KNN, GP, and SVR) are trained. In Step 2, the accuracy of the trained machine learning models is quantified with both standard evaluation metrics and the proposed new evaluation metric.

In this paper, Chapter 4 gives the details of Step 1. Chapter 5 provides details about Step 2 and the two evaluation metrics. Chapter 6 describes the validation results and discusses the differences between the two evaluation metrics. Finally, Chapter 7 is the conclusion of this study.

4. Model Training

Step 1 consists of the following processes.

- (1) Generating the training data
- (2) Training the machine learning models

This chapter describes each process in detail.

4.1. Generating the Training Data

In this study, battery floating car data (21,765,370 records) from plug-in hybrid vehicles were used to generate training data. Data were collected from vehicles that were being operated within 30 days of their first use, with little change in battery performance from initial levels. Collected data categories were battery overpotential, temperature, current, and open circuit voltage. The purpose of this study is to find an evaluation metric that can appropriately judge the relative merits of machine learning models trained with discrete data. Therefore, discrete data were generated based on the above data and used for training the models. In this study, discretization was performed with respect to temperature. At each of the following temperatures, 500 data records were randomly extracted within a ± 0.5 deg. C range: -20, -10, 0, 10, 20, 30, 40 (all deg. C). The extracted data temperature distribution is as shown in Fig. 3.

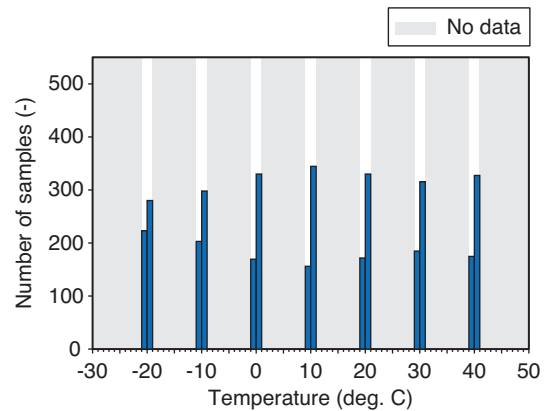


Fig. 3 Frequency histogram for temperature of training data

Table 1 Optimized hyperparameters of machine learning models

ML model	Hyperparameters
RF	n_estimators: 10; max_depth: 50
KNN	n_neighbors: 6; weights: uniform
GP	kernel function: RBF length_scale: 200; length_scale_bounds: fixed
SVR	kernel function: RBF epsilon: 0.01

4.2. Training the Machine Learning Models

The configuration of the battery overpotential estimation model is shown in Fig. 4. Battery overpotential is estimated using data gathered from vehicles and a machine learning model. The three explanatory variables of the machine learning model are the open circuit voltage, current, and temperature. The target and explanatory variables are both time-synchronized data. Four types of machine learning models were selected for use from the available supervised regression models. RF and KNN were used as the models that perform discrete estimates in regions where data are not available. GP and SVR were used as the models that are capable of continuous estimation even in regions where data are not available. The hyperparameters of the machine learning models were determined after optimization using the Hold-out Method on the training data. The optimized parameters are shown in Table 1. For other hyperparameters not shown in Table 1, the default scikit-learn 1.0.1 parameters were used⁽⁸⁾.

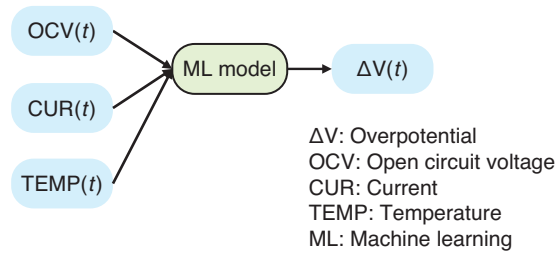


Fig. 4 Structure of machine learning model

5. Model Evaluation

In Step 2, in order to test the difference between the commonly used evaluation metric and the proposed new evaluation metric, the trained models' accuracy on the following two metrics was evaluated.

- (1) Accuracy with respect to test data
- (2) Accuracy with respect to the theoretical formula that describes overpotential

This chapter describes each evaluation metric in detail.

5.1. Accuracy with Respect to Test Data

Accuracy with respect to test data was quantified using the process shown in Fig. 5. This evaluation metric is commonly used for evaluating the accuracy of machine learning models. First, the test data explanatory variables are input into the trained model and estimated values are obtained. Then, the estimated values and test data target variables were compared, and the estimation deviation calculated. The estimation deviation was quantified with the root mean square error (RMSE) shown in Eq. (1) below.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (f_i - y_i)^2} \quad (1)$$

Here, n is the total number of records, f is the estimated value of the machine learning model, and y is the test data target variable. This evaluation metric is shown below as "RMSE_test."

As with the training data, the test data were extracted from the floating car data. At each of the following temperatures, 500 data records were randomly extracted within a ± 0.5 deg. C range: -20, -10, 0, 10, 20, 30, 40 (all deg. C) (Fig. 6). However, they were extracted without any repetitions of the data extracted for training data.

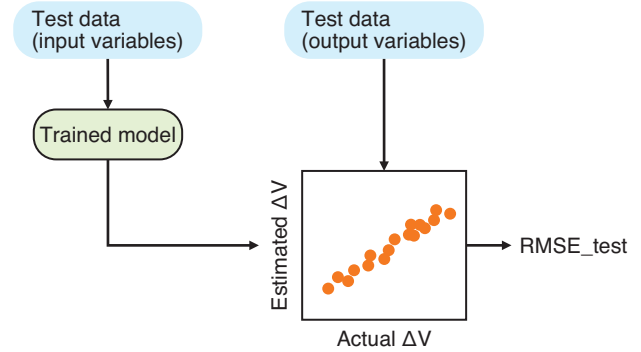


Fig. 5 Flow chart of evaluation of RMSE_test

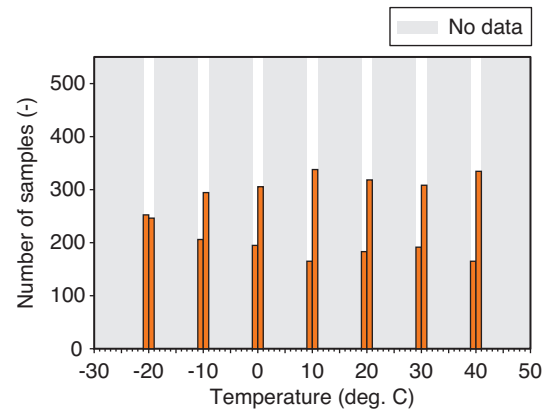


Fig. 6 Frequency histogram for temperature of test data

5.2. Accuracy with Respect to the Theoretical Formula that Describes Overpotential

Accuracy with respect to the theoretical formula that describes overpotential was quantified using the process shown in Fig. 7. This evaluation metric is the proposed new evaluation metric, the aim of which is to continuously and comprehensively evaluate machine learning models. This study targeted the temperature dependence of overpotential, which is relatively easy to determine with a theoretical formula.

For the evaluation, after continuously and comprehensively generating explanatory variables data, the generated data were input into the trained model and the estimated values were obtained. Next, the inputted virtual temperature values were plotted along the horizontal axis, and the model's estimated values along the vertical axis. With the results, fitting was performed with a function derived from the Arrhenius equation, and deviation quantified by RMSE. This evaluation metric is shown below as "RMSE_arrhenius."

The virtual data were generated by continuously changing the conditions within the expected range of usage conditions of the battery. In concrete terms, data were generated under the following patterns (671 patterns at each temperature).

- Current: 0.5 to 1.5 C, at 0.1 C intervals (11 patterns)
- Open circuit voltage: 3.5 to 4.1 V, at 0.01 V intervals (61 patterns)

Temperature conditions were generated under the following patterns.

- Temperature: -20 to 40 deg. C, at 1 deg. C intervals (61 patterns)

The generated data temperature distribution is shown in Fig. 8. A comparison with the test data temperature distribution of Fig. 6 confirms that the data are continuous and comprehensive. The machine learning model's average estimated value for all patterns at each temperature was

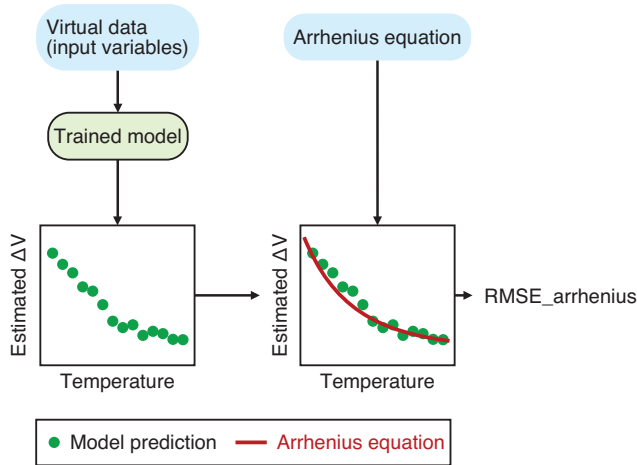


Fig. 7 Flow chart of evaluation of RMSE_arrhenius

used as the representative value for each temperature.

The Arrhenius equation was used as the theoretical equation for evaluating the temperature dependence of the machine learning model estimated values. It is known that within the internal resistances of batteries, the temperature dependence of the resistance ensuing from interfacial charge transfer resistance and slowing of ion diffusion speed follows the Arrhenius equation⁽⁹⁾. On the other hand, the electrical resistance of the current flowing through the collector and conductive material in the electrodes does not follow the Arrhenius equation. Taking the temperature dependence of these resistances into account, the temperature dependence of overpotential is considered to follow Eq. (2) below, which adds a constant term to the Arrhenius equation.

$$\Delta V = A \exp\left(\frac{-E_a}{RT}\right) + \Delta V_0 \quad (2)$$

Here, ΔV is the overpotential, R is the gas constant, T is the temperature, E_a is the activation energy, A is a temperature-independent coefficient, ΔV_0 is a constant that expresses overpotential that does not follow the Arrhenius equation. The optimization parameters when fitting the temperature dependent estimated values of the machine learning model with Eq. (2) are A , E_a , and ΔV_0 .

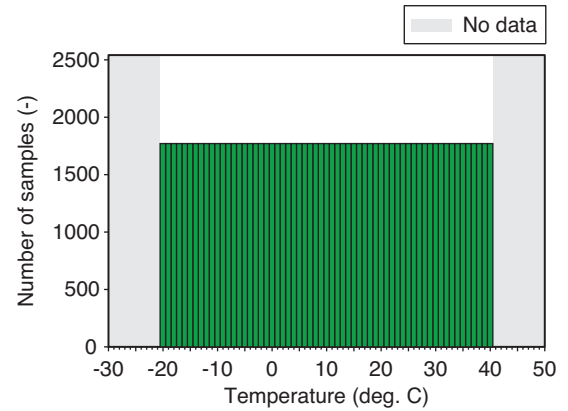


Fig. 8 Frequency histogram for temperature of generated data

6. Results and Observations

Figure 9 shows the evaluation results of the four machine learning models with the two types of evaluation metric used to determine if it is possible to judge the relative merits of the RF and KNN models, which perform discrete estimates in regions where data are not available, and GP and SVR models, which perform continuous estimation even in regions where data are not available. In generating training data and test data, a random pattern (random

seed) was repeated 32 times for training and validation. Also, the average of 32 RMSE repeats are arranged and shown for each machine learning model in Table 2. From these results, it was confirmed in the RMSE_test that the difference between the RF and KNN variance (average of 20.8 mV) and GP and SVR variance (average of 20.4 mV) was too small to enable judging of relative merits. On the other hand, with the proposed new metric, RMSE_arrhenius, the RF and KNN variance (average of 12.3 mV) was calculated at 10 times that of the GP and SVR variance (average of 1.2 mV), confirming that the difference between the two could be judged clearly.

Figure 10 shows the results when comparing the machine learning model predicted values with the test data actual values. All the results conform to a single random pattern. Based on the results, no characteristic tendency could be confirmed in any model in the test data estimation, and so it was judged that there was no difference between each model. It is thought that the reason for this is that because the temperature range of the test data is the same as the temperature range of the trained model, all the models are appropriately learning the trends of the data.

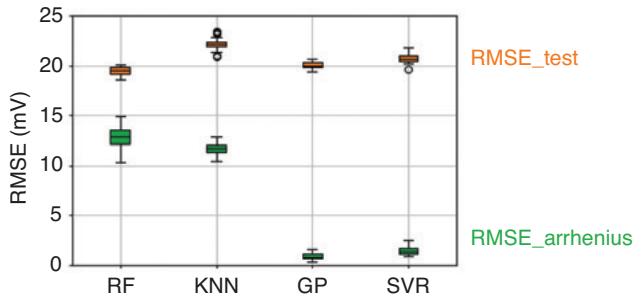


Fig. 9 Evaluation results of machine learning models

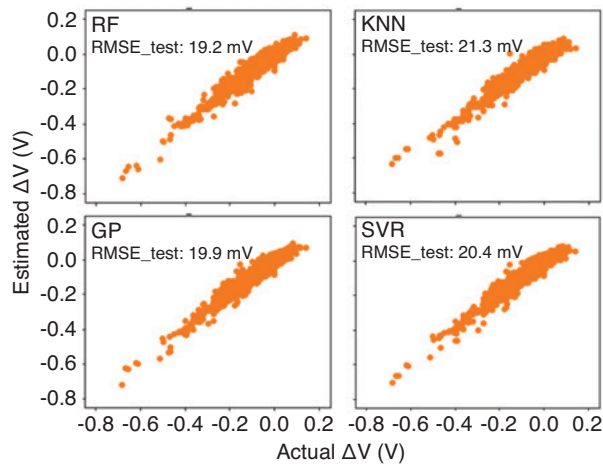


Fig. 10 Comparison of estimations of machine learning models with actual values of test data

Table 2 Evaluation results of machine learning models

ML model	RMSE_test	RMSE_arrhenius
RF	Average: 20.8 Standard deviation: 1.4	Average: 12.3 Standard deviation: 1.1
KNN		
GP	Average: 20.4 Standard deviation: 0.5	Average: 1.2 Standard deviation: 0.5
SVR		

(Unit: mV)

Figure 11 shows the results of comparing the machine learning models' estimated temperature dependent values with Eq. (2). Here, the dots show the estimation results obtained from virtual data input into trained models, shown as average values per 1 deg. C. The solid line is the fitting of the above average values, from Eq. (2). The result confirms that with the RF and KNN models, the estimated values changed discontinuously with respect to temperature changes compared to the GP and SVR models, and in relative terms, clearly deviate from the theoretical values predicted by Eq. (2). On the other hand, with the GP and SVR models, it was confirmed that the estimated values changed continuously with respect to temperature changes, and closely tracked Eq. (2) in temperature ranges from low to high.

From this result, it was confirmed that with the conventional evaluation metric (RMSE_test), it was not possible to judge the relative levels of accuracy in regions where data are not available, but with the proposed new metric (RMSE_arrhenius), it was possible to clearly judge the relative merits.

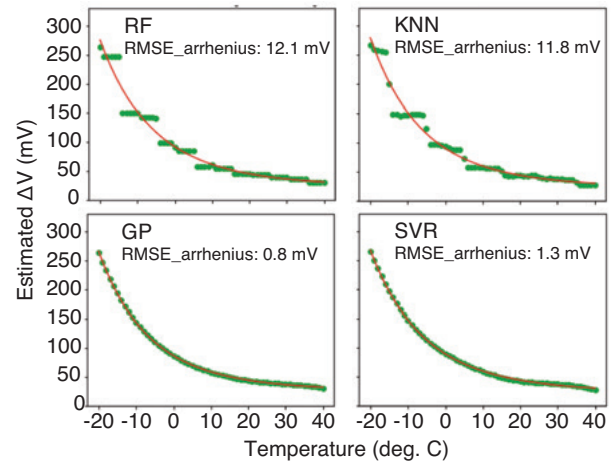


Fig. 11 Temperature dependence of machine learning model estimations compared to curves predicted from Arrhenius equation

7. Conclusion

In this paper, the authors have proposed a new evaluation metric based on an electrochemical theoretical formula (Arrhenius equation) for the evaluation of the battery voltage estimation models that use machine learning. In the study, discrete temperature data were generated from data collected from vehicles, then used to train and evaluate four types of machine learning models (RF, KNN, GP, and SVR). The result shows that with a conventional evaluation metric (RMSE targeting test data), it was not possible to clearly judge differences between RF and KNN models and GP and SVR models, but with the proposed new metric, it was possible to clearly judge the differences.

When using conventional evaluation metrics to evaluate a machine learning model, it is necessary to collect data from a large number of vehicles over a long time period, which poses issues in terms of practicality. However, the proposed evaluation metric makes it possible to evaluate a machine learning model even with limited collected data, and so this is believed to advance the practical application of battery voltage estimation technology using machine learning models. In this study, the metric was used to evaluate the temperature dependence of overpotential, which is easy to determine with a theoretical formula. However, if it possible to define a governing theoretical formula that can express the relevant trend, other variables (current, charge rate, etc.) are believed to be capable of use for the evaluation. In future studies, there are plans to look at dependence evaluations based on other variables, in addition to temperature dependence of overpotential.

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Correction of errors

No.	Vol. No.	pdf No.	Title of the paper	Page	Corrected part	Details			
1	Vol.34 No.1	34-1_04e	Development of EU3200i Handy Portable Generator	p. 30	Table 1, units	Error			
							Model name	EU2200i	EU3200i
							Max power [kVA]	2200	3200
						Rated power [kVA]	1800	2600	
						Correct			
							Model name	EU2200i	EU3200i
Max power [VA]	2200	3200							
Rated power [VA]	1800	2600							

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Editorial Afterword

Thank you very much for reading all the way through to the end of Vol. 34, No. 2, of the Honda R&D Technical Review. I am grateful for all the effort put into this issue by everyone who submitted manuscripts and all those who were involved in editing it and bringing it to publication.

I have been engaged in reviewing papers and editing the Technical Review for two years now. Frankly, I had not imagined the close attention to detail involved in bringing it to publication. This starts with confirmation of a paper's overall structure and proceeds to discussions with multiple reviewers and Technical Review staff members on the initial draft and then the second draft of a manuscript, polishing it along the way. Finally, when confirmation has come from the Editorial Committee, an issue proceeds to publication. One can imagine how heavy the load is on authors who are not accustomed to writing on a regular basis. In the end, however, it seems that when the authors take another look at their own completed works, they mostly feel a sense of fulfillment. When I receive an email from an author after an issue has been published, that is a moment when I feel glad to have been a reviewer.

It is my hope that those who are inexperienced in writing a paper will be able to savor the importance and joy of expressing their thoughts in writing. By putting something in writing, they gain formal knowledge of it. This brings their tacit knowledge to light so it can be put in order, and then new issues become visible, and they may look back and wish they had done things differently at some point. This is an experience where writers can find many opportunities in which one insight leads to another. Above all, though, might it not be that the benefit of writing is in putting one's own achievements in the form of a paper or an introduction to new technology that will stand for future generations?

If any of you have thought of trying out the experience of a new approach or subject, or revisiting past research and development material in order to try putting it into organized form, I strongly urge you to consider sending us your manuscripts.

Written sitting in the Honda R&D dining hall while trying to cool myself with a fluttering fan in the heat of this summer when the rainy season came to its earliest end in recorded history.

Shunji SUZUKI

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