Lead-Acid Battery State Sensor
～Development of a Battery Type Classification Technology by Using an Equivalent Circuit Model and a Support Vector Machine～

Noriyasu Iwane[*1], *Taiji Mitsuyama*[*1], *Yudai Tanimura*[*2]

ABSTRACT Recently, the lead-acid battery state sensor integrated vehicles have been proliferating. We, as the only single Japanese supplier of the battery state sensor, are working hard for addressing various technical requirements from automobile manufacturers, aiming at increasing our market share of the battery sensors even further. The background, in which the lead-acid battery state sensor integrated vehicles has been increasing, indicates the strong demand for a higher reliability for vehicle power system. On the other hand, the variation of batteries themselves has also increased even further as special batteries have been developed, which can stand the severe operating environment required in the mild hybrid system integrated vehicles. As a part of this technical trend, automotive manufacturers have been expecting us to develop a technology to identify special battery types for mild hybrid vehicles from normal lead-acid types. We have developed the identification technology mentioned above based on using both the equivalent circuit model learning technology which we have been developing and the Support Vector Machine jointly which, they say, is the strongest tool among current identification tools. Further, we have confirmed the good possibility sufficient for practical applications as a result of our trials.

1. INTRODUCTION

The reliability of the vehicle power source has been becoming more and more important because nowadays mild hybrid system integrated vehicles (mild hybrid vehicles) have been more common and the number and the importance of electrical accessories have increased. Along with this, it has been rapidly increasing to integrate the sophisticated lead-acid battery state sensor in a vehicle, which detects not only direct measurable values such as current, voltage or temperature but also the charge rate and the degradation level of the battery.

We have launched the Battery State Sensor (BSS) in a market as the only single Japanese supplier of the battery state sensor and are aiming at increasing our market share of the battery sensors furthermore with developing new functions aggressively. Figure 1 shows an example of BSS products.

In relation with the requirements for robustness of a vehicle power source mentioned above, variations in batteries themselves have also increased even further, such as batteries specialized for the use in the mild hybrid vehicles. Automobile manufacturers think it is ideal to apply an optimum control to each of these variations and are expecting us to integrate such functions and techniques on our BSS to identify the variations.

We have tried to develop a technology to identify a special type for mild hybrid vehicles from a normal lead-acid type by applying both the learning technology under the vehicle environment of the battery equivalent circuit model which we have developed and the Support Vector Machine (SVM)[1)] which, they say, is the strongest tool among current identification tools. Further we have reached results of the good possibility sufficient for the actual application after some validation in our laboratory. Here, we are going to report the contents.

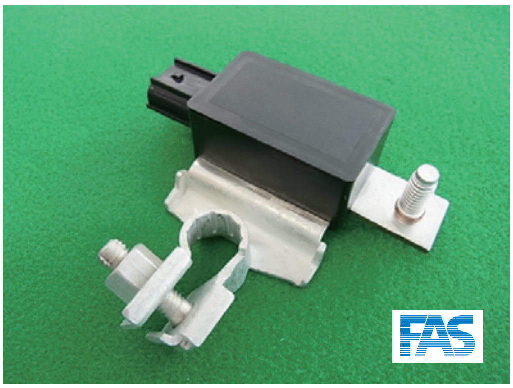

Figure 1 Battery state sensor (made by FAS).

[*1] Automotive Products & Electronics Laboratories, R&D Division
[*2] Advanced Technologies R&D Laboratories, R&D Division

2. BATTERY EQUIVALENT CIRCUIT MODEL

It is necessary to set indexes called descriptors in order to identify the type of battery as well as to detect the state of the charge rate and the degradation level. Internal resistance may be a descriptor which is most intuitionally remembered in the battery. But only with a simple one-dimensional information of internal resistance, it cannot be a practical descriptor to identify the type because the influence of the battery size and others may be added one after another. So, a more diversified index, that is to say, a multi-dimensional information is required.

For this purpose, we had already introduced the equivalent circuit model of a battery which had a multi-dimensional information in order to detect the battery state at a high accuracy. A typical equivalent circuit model is shown in Figure 2 below;

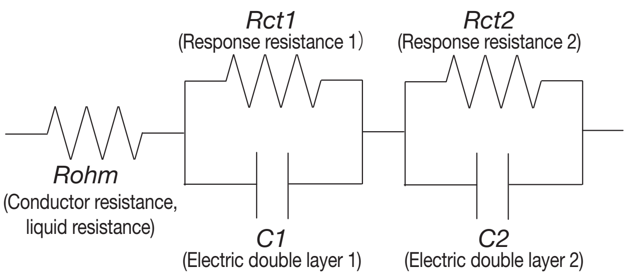

Figure 2 Example of an equivalent circuit model of a battery.

The technique, to determine an electrochemical phenomenon by applying an equivalent circuit model, has been commonly used but not only limited to batteries. There is a merit to use this technique so that we can find out the contribution of each of the components to the electrochemical reaction in a non-destructive and quantitative way. Figure 2 shows a simple example as a model, which is composed of a pure ohmic resistance with a conductor resistance and a liquid resistance and a charge-transfer resistance caused by electrochemical reaction at a positive pole and one at a negative pole respectively and an electric double layer capacitance formed on a positive pole and one on a negative pole. Further, in addition to these, such a model is commonly used as well, as the resistance caused by the concentration diffusion of the electrolyte that has been added to.

In a common technique using an equivalent circuit model, it is common to quantify each element (parameter) of the equivalent circuit model set by the Electrochemical Impedance Spectroscopy[2].

In this Electrochemical Impedance Spectroscopy, at first, using a special impedance measuring device, apply an AC current to the battery and sweep the frequency of AC current to find out the spectrum of impedance. And plot them on the complex plane to express it in the shape of the so-called Nyquist-plot. And determine the best parameter of equivalent circuit model as to reproduce the behavior of this Nyquist-plot. Figure 3 shows an example of the Nyquist-plot.

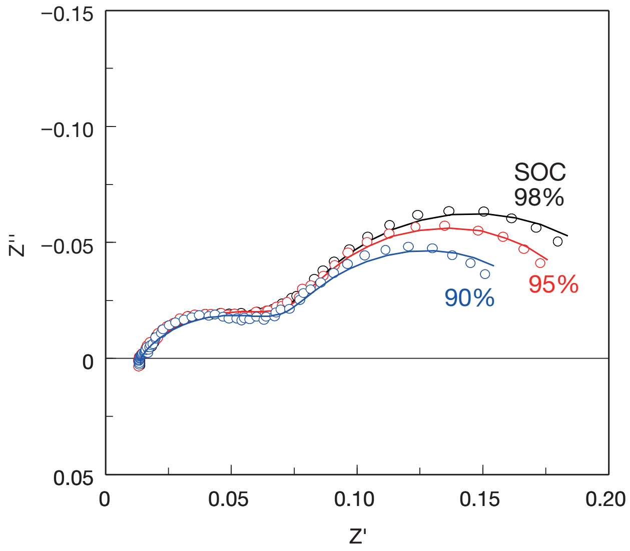

Figure 3 Example of a Nyquist-plot of a lead-acid battery.

This technique is widely used in the field of electrochemistry not only limited to batteries because the quantified parameters of the equivalent circuit model mentioned above can explain the actual phenomenon very well.

There is no particular difficulty to carry out the method mentioned above in a laboratory environment. But as for the BSS, it is necessary to learn and update regularly the parameters of the equivalent circuit model of the battery in a vehicle environment. In this case, it is impossible to carry out the traditional learning with using an impedance measuring device which includes the creation of AC sine-curve signals. Therefore, we have been developing such technology[3] that could be applied to an actual BSS, which would carry out a learning and a quantification of parameters of the equivalent circuit model as same as carried out by the impedance measuring device (Nyquist-plot) originally based on the dynamic current & voltage response in an actual vehicle environment. Its summary is as follows;

Apply a regular pulse electric discharge by a BSS to carry out a sampling of the dynamic behavior of the current & voltage response (Figure 4) at this pulse discharge and that (Figure 5) at the starting of the engine. Optimize the parameters of the equivalent circuit model in order to match the simulation calculation by the equivalent circuit model the best with the sampled data.

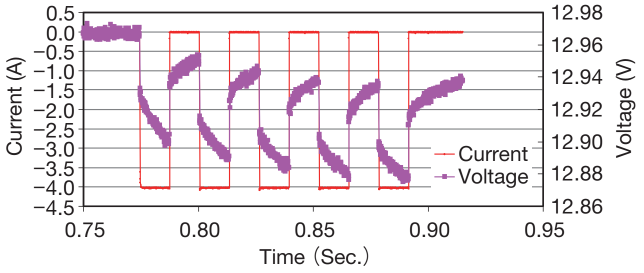

Figure 4 Example of the wave shape of a pulse discharge current and voltage.

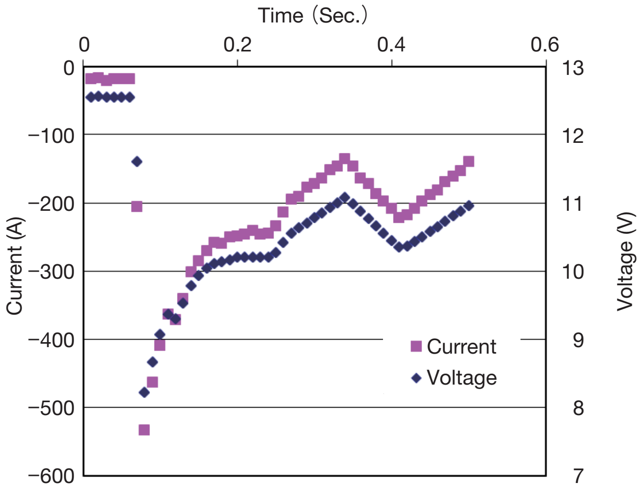

Figure 5 Example of a wave shape of a cranking current and voltage.

As mentioned above, we have been targeting at the optimization technology of the equivalent circuit model in the actual vehicle environment and the realization of a higher degree of the state detection utilizing the multi-dimensional descriptor of the equivalent circuit model. The prior purpose of this development is to identify the types of battery. As this descriptor shows the equivalent circuit model that correspond to the state of the battery, we can expect that this descriptor will function effectively as well to identify battery types which are different in their characteristics.

3. SUPPORT VECTOR MACHINE (SVM)

The proposal is called an identification problem, in which each of the descriptors is specified to belong to a group based on the data in which various descriptors from a sample group composed of 2 groups or more exist combined. This problem has been discussed in many fields. Artificial Neural Network (ANN)[4] is the most famous tool to solve this identification problem. And Convolutional Neural Network (CNN)[5], which is extended from the ANN is known to have a high identification ability especially in the image recognition. It is expected to apply the automatic driving technology in the vehicle use. In general, it is necessary that the tool has completed the learning in order to be useful as a tool for solving the identification problem. For the learning, examples of group of descriptors already known to belong to each group should be prepared as training data in advance. In particular, in order to realize highly accurate identification, it is necessary to collect enormous number of training data and learn by applying enormous computation load, in addition to designing the network. This is a weak point of ANN. Furthermore, there is such a risk that the result of learning cannot reach a global optimum solution but falls into a local optimum solution because in general, there exist limitless number of solutions for a border of identification known as a separating hyperplane

Now, the attention is focused on SVM as a tool which has overcome this weak point. Here, only a summary shall be simply shown as the details of the SVM have been already expressed in many explanations[6), 7)]. The SVM is purely a mathematical and geometrical tool different from the ANN which is a tool simulating the operation of neuron cells of human. Its basic concept is shown in Figure 6 below;

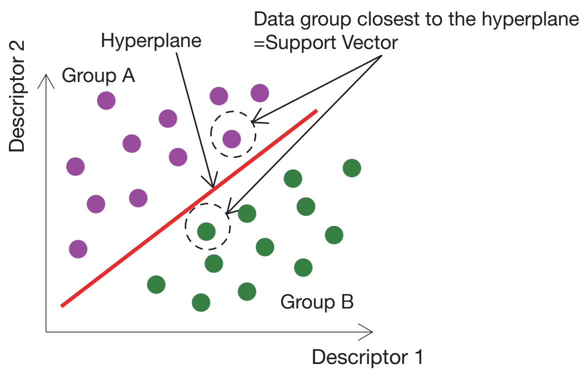

Figure 6 Basic concept of a Support Vector Machine.

An identification space composed of simple two-dimensional descriptors is shown in Figure 6. It is a feature of the SVM to determine the separating hyperplanes as to maximize the normal distance (margin) between the separating hyperplanes and the Support Vector by focusing only on a data group (Support Vector) which exists at the nearest to a separating hyperplane. With this, the volume of handling data is drastically reduced and the global optimum solution is uniquely determined. As a result of it, the SVM can be a tool having a high identification capability (high generalization capability) even for unlearnt data. The high generalization capability is one of the most important characteristics as well even in our application.

The SVM has the merit mentioned above, but on the other hand, it was very difficult to use it in the most of the non-linear identification in the world because the SVM was a linear identifier when it was invented. The SVM was inferior in this point to the ANN which is a non-liner identifier and was limited in its application. But the application of SVM spread out all at once when a technique known as Kernel-trick was invented. The basic thought of the Kernel-trick is that data are mapped to a space called the "feature space", to which a virtual dimension is added and the linearly separable plane is determined in this feature space. An image of the feature space mapping is shown in Figure 7 below;

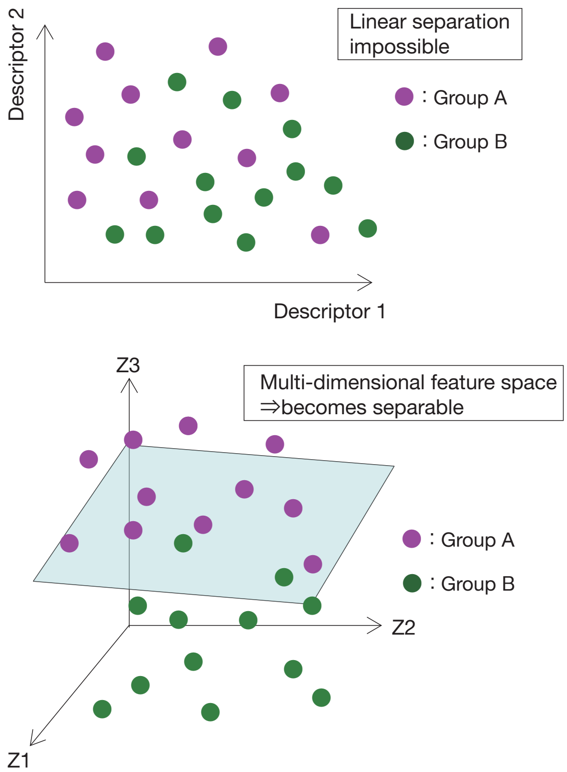

Figure 7 Image of a feature space mapping.

In general, in order to map on the multi-dimensional space, it is necessary to find the coordinates of each data in the feature space and to calculate the coordinate of the "dimensions in the feature space x number of data" as well. Further, if the dimension of the original descriptor is so high, individual calculations will be more complex and in many cases tremendous calculations may be required.

It is the feature of the Kernel-trick to replace the calculation of coordinates in the feature space with the calculation of constants of function by selecting a proper function (Kernel function) to find coordinates of added virtual dimensions in order to reduce arithmetic load drastically. Gaussian-Kernel, Laplace-Kernel and polynomial-Kernel are well known as typical functions to make the Kernel-trick work validly.

4. BATTERY GROUP OF IDENTIFICATION TARGET

As mentioned above, recently, mild hybrid vehicles have been becoming common. A battery designed exclusively for mild hybrid vehicle, which is different from a traditional lead-acid battery installed in a non-mild hybrid vehicle is installed in a mild hybrid vehicle. This battery is so designed to operate under the severe operating environment against a battery as to have endurability against frequently repeated stops and re-starts of the engine (= generator), a high regenerated charge acceptability and endurability against partial State of Charge (SOC) condition to secure the regenerated charge acceptability. On the other hand, if a traditional lead-acid battery is used in a mild hybrid vehicle, the battery may be rapidly degraded and in such an assumed case where a power failure occurs during driving a vehicle and causes an accident.

The mentioned above is an example of cases that will require the battery identification. Here, assuming this case, we have examined the possibility of identification. Table 1 shown below is a comparison table between typical batteries exclusive for mild hybrid vehicles and traditional lead-acid batteries.

Table 1 Comparison Table of between Typical Batteries Exclusive for Mild Hybrid Vehicles and Traditional Lead-Acid Batteries.

Normal Type	For Start-stop vehicle	External dimensions (Max.) / mm			
		Length	Width	Container height	Overall height
B20	M-42	197	129	204	227
B24	N-55	238	129	204	227
D23	Q-85	232	173	204	225
D26	S-95	260	173	204	225
D31	T-110	306	173	204	225

In this examination, a total of 27 types of batteries (total 184 pieces) from four Japanese manufacturers shown in Table 2 below were applied as training data.

Table 2 Batteries used as training data.

Maker	Battery type	Size
Maker A	Normal type	38B19 44B19 55B24 110D26
	For Start-stop vehicle	M-42 Q-85
Maker B	Normal type	46B24 80B24 55D23
	For Start-stop vehicle	M-42 N-55 Q-55 Q-85
Maker C	Normal type	40B19 55D23 80D23 80D26 115D26
	For Start-stop vehicle	M-42 N-55 Q-85 S-95
Maker D	Normal type	80D26 110D26
	For Start-stop vehicle	M-42 Q-85 S-95

Descriptors are parameters of equivalent circuit models as mentioned above. In this examination, we assumed the same model as that shown in Figure 2. Applying our developed logic to find out the parameters of the model, we have taken three components, *Rohm*, *Rct1* and *C1* among the parameters and let it learn these three components from the current & voltage response at pulse discharge. We have used a prototype sensor equipped with pulse discharge function and our developed logic. In this examination, we focused on examining the possibility of the identification and carried out the learning under the ideal condition free from influence of either temperature or SOC by adjusting all the batteries as max. current = 10 hour rate current and SOC = 100 % by CV charge held at 14.4 V and fixing the temperature environment at 25℃ even though we had already constructed the logic which would not be influenced by temperature or SOC in the equivalent circuit model. The 3-dimensional distribution diagram of the found-out equivalent circuit model (three descriptors) is shown in Figure 8 below;

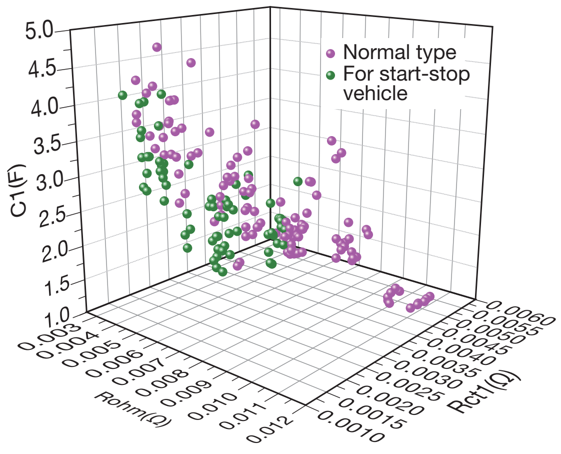

Figure 8 3-Dimensional distribution diagram of the equivalent circuit model.

5. TRIAL AND RESULT OF IDENTIFICATION

When the identification is carried out by the sensor, if only the prepared separating hyperplane is equipped in advance, the identification of battery types can be carried out by comparing the learnt equivalent circuit model and the separating hyperplane. Therefore, it is not necessary to develop an identifier special for deciding on a separating hyperplane. An identifier available in the market can be used. This time, we used the SVM Function (svmtrain function) of the Statistics Toolbox prepared as an option for the general-purpose numerical simulation software Matlab (R2014a) made by Mathworks.

When learning the separating hyperplane, the data of equivalent circuit models (*Rohm*, *Rct1* and *C1*) of the 27 types of batteries by Japanese four manufacturers shown in Table 2 are prepared as the training data. And with carrying out the svmtrain function command, the result can be output. As a matter of fact, the simplest trial would be to divide the 27 types of batteries directly into two groups and to identify them with a single separating hyperplane. However, it was estimated by checking the data in advance that it might be difficult to carry out a highly accurate identification with this technique. The example is shown in Table 3 below;

It is a general trend of battery that larger the capacity of the battery, the smaller the internal resistance and also the larger the electric double layer capacitance. We use this trend for the battery state detection. A battery exclusive for mild hybrid vehicles is designed as its internal resistance is smaller and its value of electric double layer capacitance is larger than those of the same cell-sized normal lead-acid type because it should endure the severe operating condition of the mild hybrid vehicle mentioned above. Thus, the values of the descriptors of the battery exclusive for mild hybrid vehicles with 129 mm in width (Size B of normal lead-acid type) are similar to those of 80D23 which is 173 mm in width (Size D of normal lead-acid type). Further, these values have an overlap in each of the three model parameters. So, it was estimated that practical identification might be difficult even if the mapping was carried out in the multi-dimensional space.On the other hand, as the dimension in width is different between a battery with 129 mm in width (Size B of normal lead-acid type) and one with 173 mm in width (Size D of normal lead-acid type), we may expect there must be very few possibilities that these two batter-

Table 3 Example of equivalent circuit model parameters.

Width / mm	Type	Size	Maker	Rohm / Ω	Rct1 / Ω	C1 / F
129	Normal type	46B24	Maker C	0.00807	0.00310	2.255
		55B24	Maker A	0.00682	0.00386	1.700
	For Start-stop vehicle	M-42	Maker B	0.00648	0.00226	2.543
		N-55	Maker C	0.00559	0.00292	2.573
173	Normal type	80D23	Maker B	0.00593	0.00268	2.856
		80D23	Maker D	0.00600	0.00320	2.150
	For Start-stop vehicle	Q-85	Maker B	0.00466	0.00153	2.890
		S-95	Maker D	0.00342	0.00164	4.111

ies are interchangeably used in a same vehicle. Therefore, such a simple thought can be valid that a sensor shall be able to carry out the identification either in the battery group of 129 mm width only or that with 173 mm width only. We have decided to follow this thought from the view point of examining the possibility of achievement.

Based on the thought mentioned above, dividing the parameters of the equivalent circuit model shown in Figure 8 into two groups, the training data were prepared. As mentioned above, it is necessary to select a proper Kernel function in order to map in the feature space by Kernel-trick. Major Kernel functions are already equipped in the Statistics Toolbox of Matlab. The shape of the Kernel function is reflected to the mapping in the feature space. We have mainly examined polynomial kernels as we thought a polynomial kernel was most suitable based on the distribution state of data in the 3-dimensional descriptor space shown in Figure 8. The degree of a polynomial can be optionally set. The higher the degree is, in the higher degree feature space the mapping is carried out. When mapping is carried out by a polynomial kernel from the original 3-dimensional descriptor space, it will be the mapping in (3+ n)Cn-1 dimension at an n-degree kernel. Therefore, it will be 3-dimension at 1-degree kernel, 9-demension at 2-degree kernel and 19-demension at 3-degree kernel. In general, the more the degree is increased, the less the number of errors becomes in identification. It is already demonstrated mathematically that anything can be linearly identified if the dimension is increased up to the number of data included. On the other hand, it is known that the generalization capability will decrease on the contrary when the dimension is increased. Then, we made trials to find out, up to which number the degree of the polynomial kernel shall be increased to eliminate any errors in identification. As a result, we have succeeded in realizing zero errors in identification by 3-degree kernel both in 127 mm width group and 173 mm width group.

The separating hyperplane prepared in the multi-dimensionalized space by 3-degree kernel is shown, in the original 3-dimensional descriptor space, as a cubic surface function shown below (1). The result of the identification by separating hyperplane is shown in Figure 9 with an example of a width 173 mm group.

$$\begin{aligned}
&A0 + A1 \cdot Rohm^3 + A2 \cdot Rct1^3 + A3 \cdot C1^3 \\
&+ A4 \cdot Rohm^2 \cdot Rct1 + A5 \cdot Rohm^2 \cdot C1 \\
&+ A6 \cdot Rohm \cdot Rct1^2 + A7 \cdot Rohm \cdot C1^2 \\
&+ A8 \cdot Rct1^2 \cdot C1 + A9 \cdot Rct1 \cdot C1^2 \\
&+ A10 \cdot Rohm \cdot Rct1 \cdot C1 \\
&+ A11 \cdot Rohm^2 + A12 \cdot Rct1^2 + A13 \cdot C1^2 \\
&+ A14 \cdot Rohm \cdot Rct1 + A15 \cdot Rohm \cdot C1 \\
&+ A16 \cdot Rct1 \cdot C1 + A17 \cdot Rohm + A18 \cdot Rct1 \\
&+ A19 \cdot C1 = 0
\end{aligned} \tag{1}$$

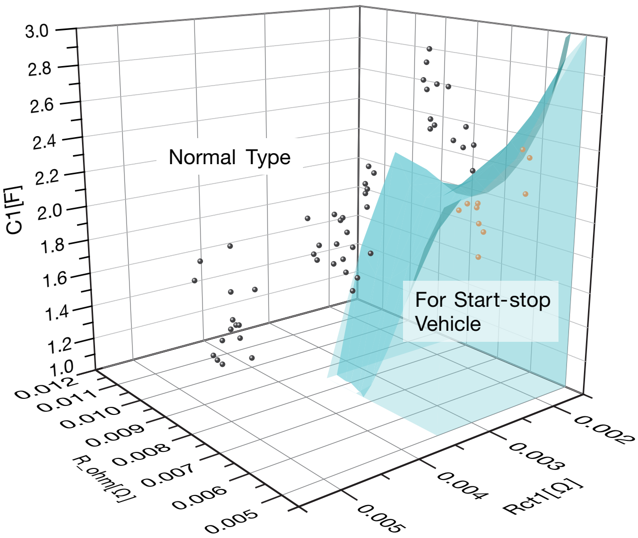

Figure 9 Example of the Result of the Identification (width 173 mm group).

6. CONCLUSIONS

Applying both the battery equivalent circuit model learning technology which we have been developing and the SVM jointly, we have got the result of realizing zero errors in identification against the prepared training data, which means we can expect its practical application. In general, a Cross-validation-test is carried out to validate the accuracy of the identification problem. But we have carried out no Cross-Validation-Test yet in this trial as the number of prepared training data was not sufficient. As batteries were optimally designed by each battery manufacturer against the required performance, it can be seen that the descriptors of the traditional lead-acid battery and of the battery exclusively for mild hybrid vehicle are separated on the both sides of the separating hyperplane of the 3-dimensional descriptor space as shown in Figure 9. The trend for other batteries than those selected for training data is never far from this trend and the identification capability for these other batteries is expected to keep better than at a certain level. However, now, we cannot say that the dimension of the feature space is low enough against the number of training data and we can say that the most important problem from now on is the validation of the generalization capability. Further, in this trial, the learning of the equivalent circuit model was carried out under such ideal condition as the temperature and the SOC condition being fixed. However, targeting the practical use, it is required to secure a so good identification capability as to absorb various errors and deviations which will occur in actual vehicle environment. We think that this is a problem to examine as well.

In this examination, as for the Kernel function which will give a major influence to the performance of the separating hyperplane, the examination was carried out mainly on the polynomial kernel only but there was no deep examination, yet. There are many cases where some

Kernel functions can be clearly judged as improper against our descriptor data based on the shape of the Gauss function such as Gaussian-kernel. As for all the prepared Kernel functions, their basic shapes have never been checked, yet. Moreover, groping for Kernel functions not prepared as tools, the higher identification capability may be realized. Examining what were mentioned above, in a near future, more improvement of performance shall be expected.

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