

Oil Temperature Classification Method for Hydraulic Electronically Controlled AWD System

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ABSTRACT

A low computational complexity and high-accuracy method for clarification of oil temperature in a hydraulic electronically controlled rear differential was developed for implementation to a vehicle control unit. Because the target system uses a motor-driven electronic hydraulic pump to increase hydraulic pressure, a correlation was considered to exist between oil temperature and motor current. Theoretical analysis of the structure of the system demonstrated that a linear model was sufficient for clarification of the state of oil temperature from motor current, and a clarification model for the state of oil temperature using logistic regression was formulated. In addition, in order to balance accuracy and frequency of clarification, a method of calculation of posterior probability when continuous multiple clarifications were executed using only the output of the logistic regression model was developed. The results of application of the method to data obtained from the actual target system confirmed that the proposed method was able to clarify the state of oil temperature with a high degree of accuracy.

1. Introduction

The performance of systems that use oil for control or cooling is significantly affected by the characteristics and the state of the oil in the system. Focusing on the effect of oil temperature on the output of an AWD system⁽¹⁾, the research discussed in this paper obtained oil temperature data using an oil temperature sensor, and used this data as a control parameter. Figure 1 shows the configuration of the rear differential used in the AWD system. Using an FF vehicle as a base, this system transmits drive power from the front wheels to the rear wheels, and is able to switch between 2WD and AWD by means of appropriate allocation of drive power between the front and rear wheels. The drive power of the front wheels is input to the rear differential via a propeller shaft; the input torque is transmitted to the rear wheels via hypoid and differential gears by means of the engagement of a clutch positioned between a clutch guide and a clutch hub. Clutch connection force can be generated as desired by controlling oil pressure using an actuator (motor and solenoid valve), and using the generated oil pressure to change the clutch control oil pressure in the system. The system has three operating statuses: pressure increase, pressure maintenance, and pressure reduction. When clutch control oil pressure is needed, the solenoid valve is closed and the motor is operated in order to

increase pressure (pressure increase); when the system judges that the control operation has been completed, the motor is stopped and oil pressure is maintained (pressure maintenance). Following this, when there is no longer any need for clutch control oil pressure, the solenoid valve is opened and pressure is reduced (pressure reduction).

If the viscosity of the oil changes, the shear resistance and friction force of the oil film between the clutch plates also changes, and this results in changes in the torque transmitted to the rear wheels. Because of this, readings from an oil temperature sensor are used as one of the parameters to determine the necessary clutch control oil

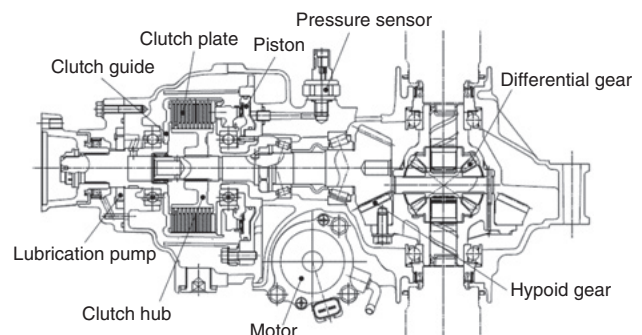


Fig. 1 Structure of rear differential system

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pressure (“target clutch control oil pressure”). When the oil temperature sensor is operating normally, no issue is presented, but if, for example, a sensor malfunction were to result in an abnormal value being output, there would be a divergence between the true target clutch control oil pressure and the target clutch control oil pressure that is calculated on the basis of a variety of parameters. If the vehicle were driven when the target clutch control oil pressure was not calculated correctly, vehicle behavior could become unstable. In particular, if the oil temperature sensor outputs an abnormal value when the oil temperature is low, it is possible that excessive torque might be applied to the gears in the rear differential, and this could affect their durability. It is therefore necessary to judge whether the present oil temperature in the system is low using a separate method to the oil temperature sensor.

A variety of estimation methods and judgment methods have been proposed in order to obtain data concerning the physical characteristics of the oil. Of these, previous research has indicated the practicality of methods employing machine learning. Because when machine learning is used it is possible to create a model based solely on the data that the user wishes to model, this method has the merit of making it possible to produce models even in situations in which obtaining direct knowledge of the internal structure of the system under study represents a challenge. Balabin et al. proposed methods of classifying mineral and synthetic oils and of classifying viscosity in oils used in an engine by applying the k-nearest neighbor (k-NN), neural network (ANN) and support vector machine (SVM) methods to absorption spectrum data obtained by means of near-infrared spectroscopy⁽²⁾. In addition, a number of reports have been published concerning methods of estimating the temperature of the insulating oil in oil-immersed transformers utilizing ANN that learns from the transformer load and the ambient air temperature⁽³⁾⁻⁽⁵⁾. Other research focusing on oil-immersed transformers has taken the amount of gas in the oil as a feature quantity, and classified abnormal states in on-load tap switches using logistic regression and ANN⁽⁶⁾. This paper indicates that the ANN approach is the more effective, given the fact that this method displays higher classification accuracy than logistic regression.

These reports demonstrate that it is possible to estimate oil characteristics with a high degree of accuracy using ANN and SVM. Because ANN and SVM employ non-linear models, high-accuracy estimation and classification is possible even in the case of data for which relationships of correlation are complex. However, the other side of this is that when results are output, it is necessary to calculate large numbers of non-linear functions (activation functions and kernel functions) by means of numerical calculation. In addition, in the case of SVM, it is necessary to store support vector data in the memory. Given the fact that in many cases real-time calculation is prioritized in the field of automotive control, these methods cannot be considered desirable from

the perspectives of computational complexity and allocation of resources. In addition, if the methods are applied, how to judge the reliability of the output figures remains an issue.

The research discussed in this paper therefore developed a highly accurate and reliable method for the classification of oil temperature in AWD systems, while controlling computational complexity. The details of this development are discussed below.

2. Oil Temperature Classification Method

2.1. Relationship between Oil Temperature and Motor Current

The research discussed here focused on the relationship between oil temperature and motor current, and developed a method of classifying the state of oil temperature by modeling the correlation between data for the two parameters. The pressure adjustment mechanism in the target system rotates rotors attached to the end of the motor by transmitting current to the motor, and draws up oil using the principle of a trochoid pump (Figs. 2 and 3). As

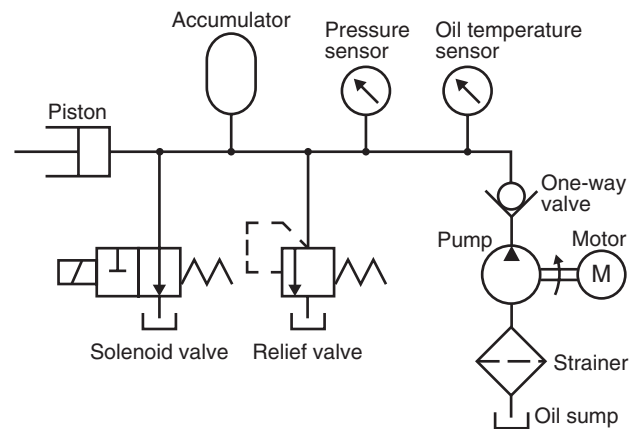


Fig. 2 Schematic of target system

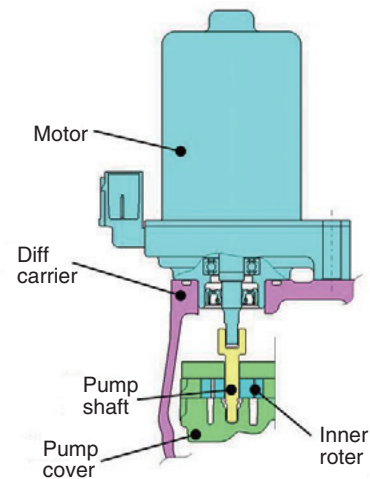


Fig. 3 Cross-section view of motor pump

indicated above, the viscosity of oil displays a temperature characteristic, with viscosity being higher the lower the temperature of the oil. It is considered that the friction in the rotors is also affected by this characteristic. In addition, due to the characteristics of the motor, there is a linear relationship between the current supplied to the motor and the torque that it produces. Because of this, it is considered that there is also a correlation between motor current and oil temperature when oil pressure is being increased (Fig. 3).

First, in order to clarify the relationship between oil temperature and motor current, the relationship was formularized using system parameters. Taking the transient state directly following the transmission of the operational command to the motor, motor current $I_1(t)$ and $I_2(t)$ can be expressed by

$$I_1(t) = \frac{V}{R} \left(1 - e^{-t/\tau_1} \right) \quad (1)$$

$$I_2(t) = \frac{1}{R} \left\{ V + \left[\frac{R}{K_T} Tq(t, temp) + V \right] \times \left[1 - e^{-t/\tau_2} \right] \right\} \quad (2)$$

where

- V : Motor drive voltage
- R : Motor resistance
- K_T : Motor torque constant
- Tq : Motor output torque
- τ_1, τ_2 : Time constants dependent on motor characteristics
- $temp$: Oil temperature
- t : Time

Figure 4 shows an outline of the current waveforms for Eqs. (1) and (2). Next, using Eqs. (1) and (2), the integrated value for current for the period from $t=0$ to $t=T$ is calculated. Because a current corresponding to the lock current is flowing at $t=T_1$, T_1 can be regarded as a constant; by further taking the integrated time T to be an arbitrary constant, the integrated value for current can be expressed as follows.

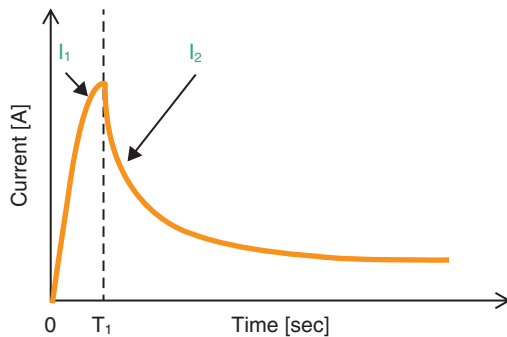


Fig. 4 Current waveform model

$$\begin{aligned} & \int_{t=0}^T [I_1(t) + I_2(t)] dt \\ &= \frac{V}{R} \left[T_1 + \tau_1 \left(e^{-T_1/\tau_1} - 1 \right) \right] + \frac{V}{R} (T - T_1) \\ &+ \frac{1}{R} \left[\frac{R}{K_T} \int_{t=0}^{T-T_1} Tq(t, temp) dt - V \right] \left\{ (T - T_1) + \tau_2 \left[e^{-(T-T_1)/\tau_2} - 1 \right] \right\} \\ &= c_1 V + c_2 \int_{t=0}^{T-T_1} Tq(t, temp) dt \end{aligned} \quad (3)$$

Here, c_1 and c_2 are constants.

Taking into consideration situations in which temperature is an arbitrary value in Eq. (3), the integral term for motor drive torque can be regarded as a constant, and Eq. (3) becomes

$$\int_{t=0}^T [I_1(t) + I_2(t)] dt - c_1 V = const \quad (4)$$

Equation (4) indicates that when data for which the oil temperature is identical has been isolated from three-dimensional data for the integrated value of current, motor drive voltage, and oil temperature, the two-dimensional data for the integrated value of current and the motor drive voltage included in that data will be linear. Put another way, it shows that when an oil temperature classification model that uses the integrated value of current and motor drive voltage as feature quantities is formulated, the boundaries for classification will be linear. This fact indicates that rather than using non-linear models such as ANN or SVM for the classification model, it is sufficient to use linear models that entail lower computational complexity.

2.2. Creation of Classification Model

Based on the results discussed above, a two-class classification model (classifying oil temperature as low or not low) using logistic regression was formulated that outputs the state of oil temperature following input of the integrated value of current and the motor drive voltage. Logistic regression is a form of standard linear modeling, and is a classification method that is robust against outliers (values significantly removed from other values)⁽⁷⁾.

The logistic regression model is expressed as

$$LOG = \frac{1}{1 + \exp(-\mathbf{w}'\mathbf{x})} \quad (5)$$

where

- $\mathbf{x}$: Input data vectors
- $\mathbf{w}$: Parameter vectors
- LOG : Class posterior probability

$\mathbf{x}$ represents the two-dimensional vectors of the integrated value of current and the motor drive voltage, and LOG is the probability of the oil temperature being above (or below) the threshold value. $\mathbf{w}$ represents the parameters that determine the behavior of the model, and its value can be calculated from data for the integrated value of current,

motor drive voltage, and state of oil temperature by means of the process described below.

First, the true state of oil temperature in each set of data is designated t . Because there are two classification classes, if $t \in \{0, 1\}$, the likelihood function for L data can be expressed by the following equation.

$$p(\mathbf{t}|\mathbf{w}) = \prod_{i=1}^L LOG_i^{t_i} \{1 - LOG_i\}^{1-t_i} \quad (6)$$

Here, $\mathbf{t}$ represents the vectors for the true state of oil temperature, and LOG_i is the figure generated by Eq. (5) for $\mathbf{x}_i$. If the negative logarithm of the likelihood function is defined as the error function $E(\mathbf{w})$, then from Eq. (6), $E(\mathbf{w})$ is expressed as

$$E(\mathbf{w}) = -\ln p(\mathbf{t}|\mathbf{w}) \\ = -\sum_{i=1}^L \{t_i \ln LOG_i + (1-t_i) \ln (1-LOG_i)\} \quad (7)$$

The value being sought is the value for $\mathbf{w}$ that will minimize Eq. (7), and this can be determined using the Newton-Raphson method by means of the following iterative calculation.

$$\mathbf{w}_{s+1} = \mathbf{w}_s - \mathbf{H}^{-1} \nabla E(\mathbf{w}) \quad (8)$$

Here, s is the number of iterations, and $\mathbf{H}$ is the Hessian matrix found from $\nabla^2 E(\mathbf{w})$. Because $\mathbf{H}$ is a positive definite matrix in the case of the logistic regression model defined by Eq. (5), in Eq. (7) $\mathbf{w}$ is a convex function, and the global optimum solution and the local optimum solution correspond. Therefore, the value of $\mathbf{w}$ determined by convergence via iterated calculation using Eq. (8) is the parameter to be sought. When $\mathbf{w}$ is determined, $\mathbf{x}$ is substituted in Eq. (5), and judgment of whether LOG is higher (or lower) than the threshold value makes it possible to output an oil temperature classification result.

In the case of the normal logistic regression equation, Eq. (5), probabilities can only be output for inputs of single units of data. This results in a trade-off, in which the potential for mistaken classification is increased if the threshold value for classification is lowered, but classification represents more of a challenge if the value is raised. A calculation method able to output probabilities when multiple data is input was therefore introduced in order to balance classification accuracy and classification frequency.

First, two units of input data, $\mathbf{x}_1$ and $\mathbf{x}_2$, were introduced in order to expand Eq. (5), and the determination of the posterior probability when oil temperature is classified as low for both (expressed as $y=1$) was considered. From Bayes' theorem, the posterior probability $p(y=1|\mathbf{x}_1, \mathbf{x}_2)$ can be expressed as

$$p(y=1|\mathbf{x}_1, \mathbf{x}_2) \\ = \frac{p(\mathbf{x}_1|y=1)p(\mathbf{x}_2|y=1)p(y=1)}{p(\mathbf{x}_1, \mathbf{x}_2)} \quad (9)$$

Because, despite the fact that $\mathbf{x}_1$ and $\mathbf{x}_2$ are in the same class, the oil temperature can be considered to change with the passage of time, conditional independence is assumed for $\mathbf{x}_1$ and $\mathbf{x}_2$ here.

Next, the output of logistic regression of $\mathbf{x}_1$ is considered as LOG_1 , and transformed as follows in accordance with Bayes' theorem.

$$LOG_1 = p(y=1|\mathbf{x}_1) \\ = \frac{p(\mathbf{x}_1|y=1)p(y=1)}{p(\mathbf{x}_1)} \quad (10)$$

Similarly, the output of logistic regression of $\mathbf{x}_2$ is considered as LOG_2 , and can be expressed as

$$LOG_2 = \frac{p(\mathbf{x}_2|y=1)p(y=1)}{p(\mathbf{x}_2)} \quad (11)$$

In addition, using Eqs. (10) and (11), Eq. (9) can be expressed as follows.

$$p(y=1|\mathbf{x}_1, \mathbf{x}_2) = \frac{LOG_1 \times LOG_2}{p(y=1)} \frac{p(\mathbf{x}_1)p(\mathbf{x}_2)}{p(\mathbf{x}_1, \mathbf{x}_2)} \quad (12)$$

Further, by means of identical calculations, $p(y=0|\mathbf{x}_1, \mathbf{x}_2)$ can be expressed as

$$p(y=0|\mathbf{x}_1, \mathbf{x}_2) \\ = \frac{(1-LOG_1) \times (1-LOG_2)}{p(y=0)} \frac{p(\mathbf{x}_1)p(\mathbf{x}_2)}{p(\mathbf{x}_1, \mathbf{x}_2)} \quad (13)$$

Based on Eqs. (12) and (13) and $p(y=1|\mathbf{x}_1, \mathbf{x}_2) + p(y=0|\mathbf{x}_1, \mathbf{x}_2) = 1$,

$$\frac{p(\mathbf{x}_1)p(\mathbf{x}_2)}{p(\mathbf{x}_1, \mathbf{x}_2)} \\ = \frac{p(y=1)}{LOG_1 \times LOG_2 + (1-LOG_1) \times (1-LOG_2)} \quad (14)$$

Because data concerning the posterior probabilities $p(y=1)$ and $p(y=0)$ cannot be obtained, here it is assumed that $p(y=1)=p(y=0)$. Substitution of Eq. (14) into Eq. (12) makes it possible to express the posterior probability when $\mathbf{x}_1$ and $\mathbf{x}_2$ are given by means of the following equation.

$$p(y=1 | \mathbf{x}_1, \mathbf{x}_2) = \frac{LOG_1 \times LOG_2}{LOG_1 \times LOG_2 + (1 - LOG_1) \times (1 - LOG_2)} \quad (15)$$

In addition, conducting identical calculations makes it possible to express the posterior probability when n units of data $(\mathbf{x}_1, \dots, \mathbf{x}_n)$ are input as

$$p(y=1 | \mathbf{x}_1, \dots, \mathbf{x}_n) = \frac{\prod_{i=1}^n LOG_i}{\prod_{i=1}^n LOG_i + \prod_{i=1}^n (1 - LOG_i)} \quad (16)$$

A value higher than the classification threshold for logistic regression is introduced as the threshold value for Eq. (16), and the classification result generated by Eq. (16) is considered to be the final classification result. By this means, an algorithm capable of instantaneously determining a classification result when data of a high degree of reliability is input, and of determining a classification result when data of ordinary reliability is input continuously, has been realized using only the output of logistic regression. Figure 5 shows the increase in the posterior probability as data is added, in accordance with Eq. (16). Figure 5 shows a case in which data containing values higher than the classification threshold value for logistic regression is continuously input. Classification is determined when the posterior probability exceeds the high threshold value. Figure 6 shows the complete flow of the algorithm.

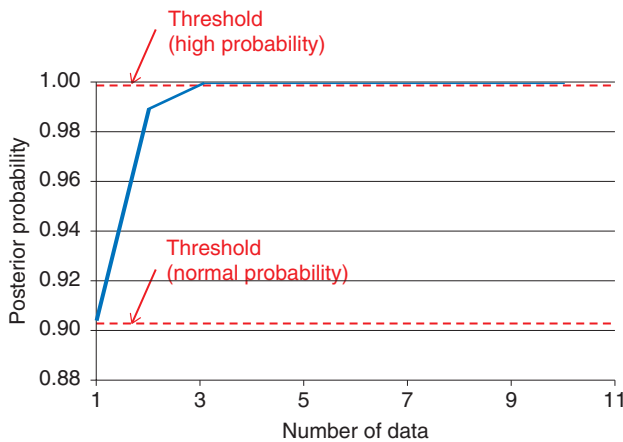


Fig. 5 Example of transition of posterior probability

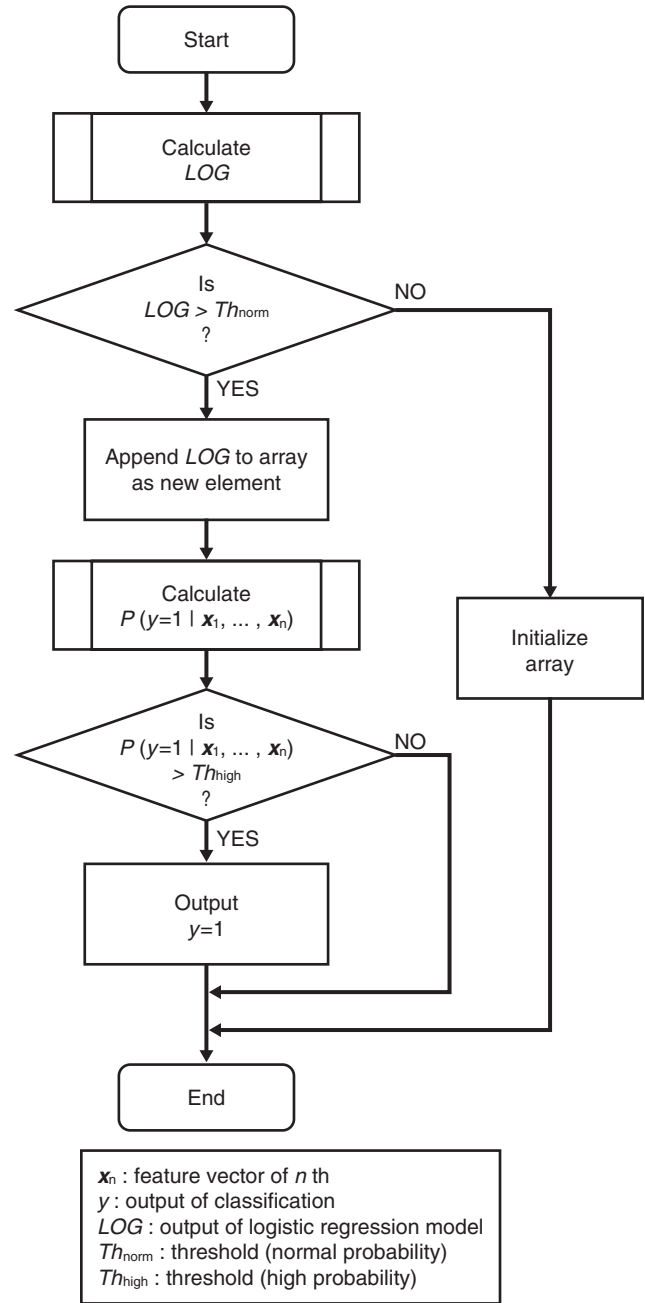


Fig. 6 Algorithm of proposed method

3. Results of Tests

Using data obtained from an actual system, a model for the classification of oil temperature as exceeding the threshold value or not was created, and the classification rate was evaluated. For the formulation and evaluation of the model, three-dimensional data for the integrated value of current, motor drive voltage, and oil temperature was used, and ten-fold cross-validation was conducted. (In this method, the data set is divided into 10, with nine units of data being used in the formulation of the model and the

Table 1 Classification rate of logistic regression

Threshold (°C)	Training		Test	
	Mean	Min	Mean	Min
20	0.974	0.973	0.973	0.960
10	0.985	0.984	0.985	0.982
0	0.982	0.982	0.982	0.977
-10	1.000	1.000	0.999	0.999
-20	0.999	0.999	0.999	0.997
-30	0.996	0.995	0.996	0.992

Table 2 Computing time comparison

Logistic regression	ANN	SVM
0.14 ms	0.23 ms	0.41 ms

remaining one unit of data used for the evaluation of the model's performance. This is repeated 10 times. The nine units of data are termed "training data," and the remaining one unit of data is termed test data). The period for integration of the current was set at 150 ms. Table 1 shows the classification results generated by the logistic regression model. The "Training" columns show the classification rate for the training data, and the "Test" columns show the classification rate for the test data. In the respective categories, the "Mean" column shows the median value for the classification rate obtained by cross-validation, and the "Min" column shows the lowest classification rate.

First, the results for the training data indicate that the state of the oil temperature can be classified with a high degree of accuracy even when a linear model is used. For the system under consideration, high classification accuracy at low temperatures is a specific goal, and the results indicate the realization of this goal, with classification accuracy increasing with decreasing temperature. This is considered to be due to the fact that the change in the viscosity of the oil in relation to temperature becomes greater the lower the temperature, which results in an increase in the rate of classification of data close to the threshold value.

The classification rate for test data also compared favorably with the results for training data for all threshold temperatures. This indicates that the generated model possesses a high level of generalization capability, and demonstrates the fact that the method has successfully produced a model able to make correct classifications even in relation to new, previously unknown data. The combination of the output of a logistic regression model and the algorithm provided by Eq. (16) has made it possible to realize more accurate classification.

Next, classification models for this specific classification challenge were formulated using logistic regression, ANN and SVM, and their calculation time for classification calculations in relation to 3000 units of data was measured. The results are shown in Table 2. For the measurements, non-linear models that would maintain classification accuracy while reducing computational complexity were selected for ANN

and SVM. For the ANN model, the evaluation was conducted using a two-layer network with two hidden units (two inputs, two hidden units, and one output), in order to indicate the differences between the model and a standard linear model. The results demonstrate that the selection of a logistic regression model as a classification model is able to reduce computational complexity in comparison to the selection of ANN or SVM models.

4. Conclusion

A method of classifying the state of oil temperature in an electronically controlled AWD system was developed and its effectiveness verified. Formularization of the motor current waveform and determination of the fact that the relationship between the integrated value of current and the motor drive voltage when the oil temperature is fixed is linear in the data space made it possible to select a classification method possessing the necessary functions to satisfy the purpose at the same time as controlling computational complexity. In addition, the reliability of multiple classification results was quantitatively evaluated, and an algorithm that outputs final classification results was formulated using only output from the classification model, resulting in the realization of a method that controls computational complexity and balances the reliability of final classification results and classification frequency.

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