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Off-line PD Model Classification of Traction Motor Stator Coil Using BP

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Abstract - Insulation failure of traction motor stator coil depends on the continuous stress imposed on it and knowing its insulation condition is an issue of significance for proper safety operation. In this paper, application of the NN (Neural Network) as a scheme of the off-line PD (partial discharge) diagnosis method that occurs at the stator coil of a traction motor was studied. For PD data acquisition, three defective models were made; internal void discharge model, slot discharge model and surface discharge model. PD data for recognition were acquired from a PD detector. Statistical distributions and parameters were calculated to perform recognition between model discharge sources. These statistical distribution parameters are applied to classify PD sources by the NN with a good recognition rate on the discharge sources.

Keywords: BP, Classification, Partial discharge, Stator coil

1. Introduction

Today, railroad transportation has some merits as compared to other types of transportation; mass transportation, accurate on time, low pollution, agreeableness, etc. But, the traction motor of the EMU (electric multiple unit) for high capability and high speed has a problem with insulation reliability caused by transient surge and partial over-heating because it has the chance to develop to the point of degradation, leading to insulation failure. This insulation failure can be caused by occurred PD from some defects of the insulated stator coil of the traction motor. The PD phenomena in the stator coil create a variable path from some of the defects; slot discharge, void discharge (internal discharge of insulator), surface discharge, etc.

However, estimation of the PD sources is a very difficult thing to carry out. Why is PD so important? Although the magnitude of such discharges is usually small, they cause progressive deterioration and may lead to ultimate failure. Therefore, PD detecting and discriminating discharge sources are crucial to maintaining the flow of continuity in a railway system. It is important to use PD distribution for estimating some defects because it contains a great deal of information on coil condition.

We composed three defected PD occurrence models; void discharge of the insulator, surface discharge, and slot discharge. PD data was acquired from the PD detecting method, IEC 270, and used to calculate statistical distribution. We then studied PD distribution characteristics on three defected PD models and used these characteristics as input data of the BP (back propagation) algorithm for classification of PD sources.

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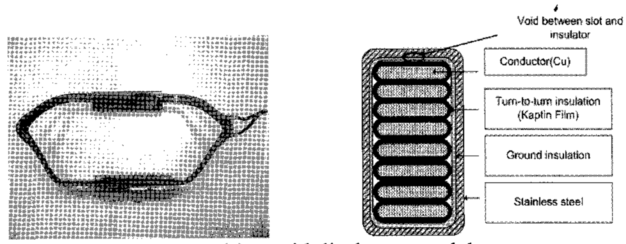
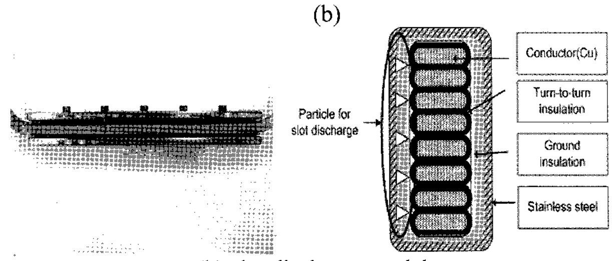
2. Experimental

2.1 Specimens for PD occurrence

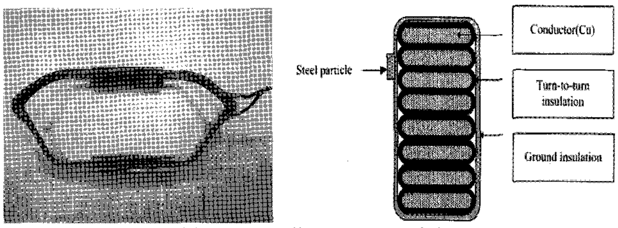
Fig. 1 shows the stator coil shape of the traction motor and cross sectional viewer of specimens of three models. The specimens are made with polyamide and silicon resin and processed by VPI (vacuum pressure impregnation) treatment.



(a) void discharge model
(b)



(b) slot discharge model



(c) surface discharge model

Fig. 1 Cross sectional viewer and PD model shape

2.2 Test procedure and data process

PD signals were collected with the PD detector system (BIDDLE instrument, AVTM 662700Ja), which is a computer controlled system for PD data acquisition and analysis. According to IEC 270, the PD pulses are integrated where the maximum value of the integrated signal is proportional to the apparent charge. Fig. 2 shows a block diagram of the PD data acquisition and process.

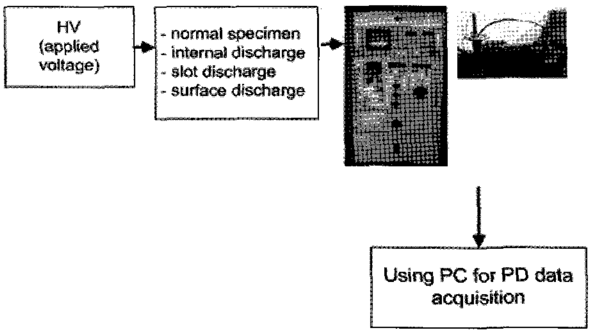


Fig. 2 Block diagram of test procedure for acquisition of PD data

Statistical distributions were calculated from original PD signals and the distributions were used as BP input data. Fig. 3 illustrates the procedure of PD data for calculating statistical distributions.

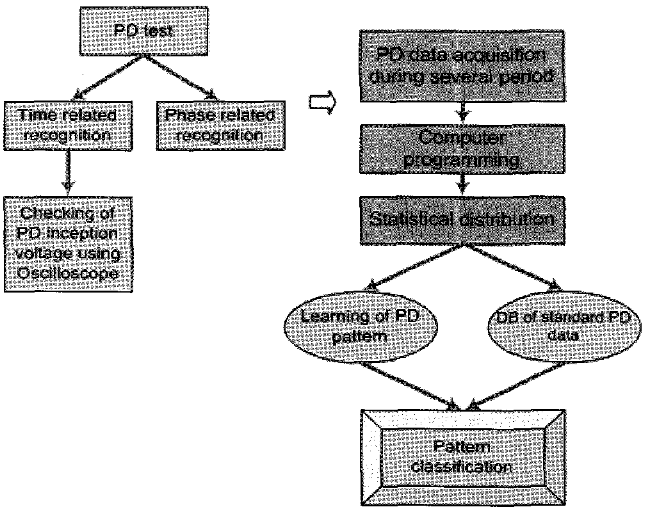


Fig. 3 Block diagram of PD data process

3. Result

3.1 PD signal distribution

The relationship between the PD magnitude and intensity as related to PD phase angle can be displayed using either a two or three dimensional pattern. Three dimensional distributions as compared to two dimensional distributions might better discriminate PD appearance and have the advantage of visible classification. But three dimensional distributions are more complex. Furthermore, three dimensional distributions are difficult to analyze quantitatively. In general, for convenience of comparison, two dimensional distributions have been chosen for use. And the BP network is applied as a learning scheme. These distributions were derived from statistical distributions of individual PD events by taking appropriate averages. Three dimensional distributions are φ(phase) - (discharge magnitude) - n(number of pulse). And two dimensional distributions are q-n, φ-qa(average discharge magnitude), φ-n, φ-q_{max}(maximum discharge magnitude) distributions. Two dimensional distribution totally can be presented as four types; Hn(q), Hn(φ), Hqn(φ) and Hq(φ).

Hn(q) distribution presents pulse count distribution, which represents the number of observed dis-charges in each discharge magnitude.

Hn(φ) distribution presents pulse count distribution, which represents the number of observed discharges in each phase window as a function of the phase angle.

Hqn(φ) distribution presents the mean pulse height distri-bution, which represents the average amplitude in each phase window as a function of the phase angle.

Hq(φ) distribution presents the maximum pulse height distribution, which represents the maximum amplitude in each phase window as a function of the phase angle.

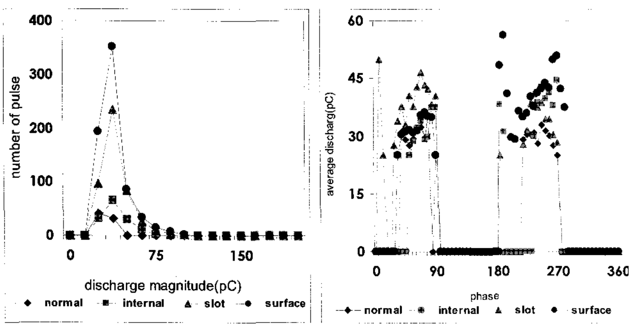
Fig. 4 presents two dimensional distributions calculated from φ -q-n distribution.

Hn(q) distribution presents surface discharge characteristic bigger than other discharges.

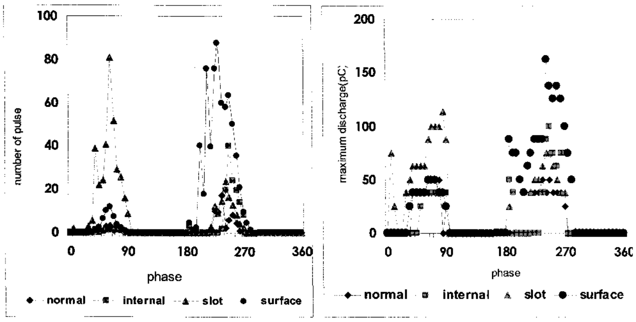
Hqn(φ) distribution is similar to all discharge sources, but surface discharge is slightly more than other types of discharge in the negative period.

Also, Hn(φ) distribution in negative half cycle surface discharge shows to be remarkably bigger than other types of discharge. However, in positive half cycle, slot discharge has a remarkably big value. Finally, Hq(φ) distribution has similar characteristics to Hn(φ) distribution.

In conclusion, surface discharge and slot discharge have extraordinarily large value on PD magnitude and number of PD pulses. But void discharges have a very small value compared to the other two discharge sources. In this paper we used q-n and φ-n distributions as input data of the BP learning algorithm because these distributions have good information among PD sources.



(a) Hn(q) distribution (b) Hqn(φ) distribution



(c) Hn(φ) distribution (d) Hq(φ) distribution

Fig. 4 Distribution of PD signal

4. Comparison of two methods

4.1 Selection of PE

As a BP algorithm, PE (processing elements) is an important parameter because PE affects the learning result.

The hyperbolic tangent function was evaluated replacing the logistic function. This function shows its RMSE result, which has 1,000 epochs for making RMSE less than 0.1. This epoch is tiny compared to the logistic function. Next, the neuron number of hidden layers was determined. Each of 10, 20, 100, 150, 200 and 300 neurons of hidden layers were investigated as shown in Fig. 5. Each result draws different curves in the region of less than 400 epochs but it approaches similar values near 1,000 epochs. 10 and 20 neurons have reached to the least RMSE value and have been selected as the neuron number of hidden layers. BP learning is sensitive to initial weighted value. If the value is incorrectly selected, BP learning is driven to the local minimum point. To investigate the effect of the initial weighted value for BP learning, initial weighted values of 0.1, 0.3, 0.5, 0.7 and 0.9 are used. And the results are shown in Fig. 6 (a) and (b). Initial weighted value of 0.1 has the least RMSE. And Fig. 7 (a) and (b) present the results of selection learning rate. Completed ANN (artificial neural network) by BP learning constructed consists of input layer (250), hidden layer (10), output layer (2), active function (tanh) learning rate (between 0.1 and 0.2) and initial weighted value (0.1). Train data set for BP learning and classification data set for evaluating the performance of ANN classification are each 50 set per PD source with the total set at 400.

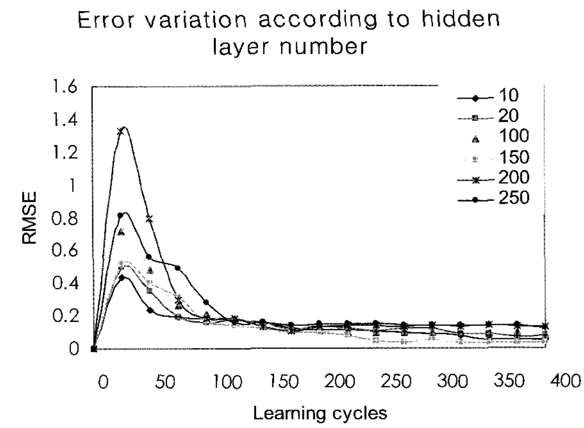
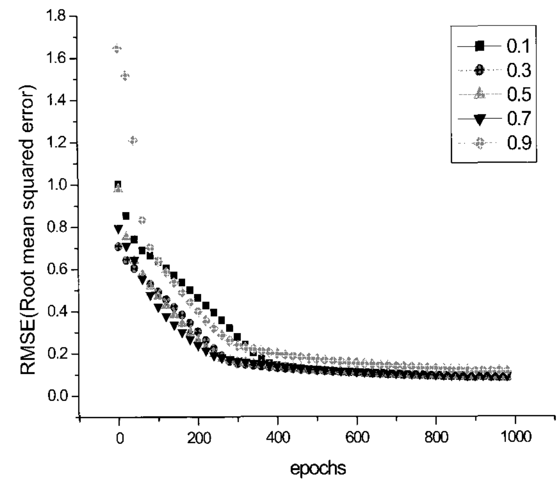
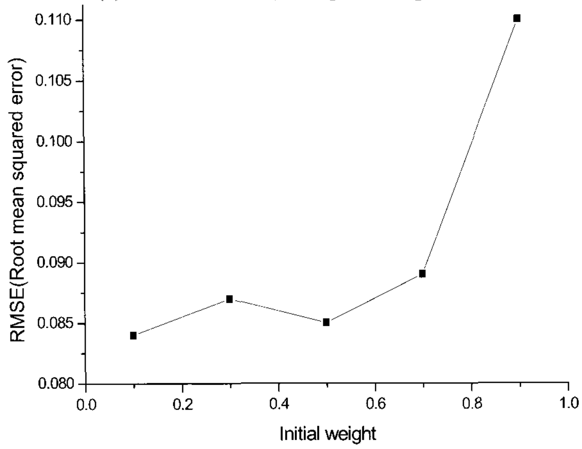


Fig. 5 Error variation according to hidden layer node number

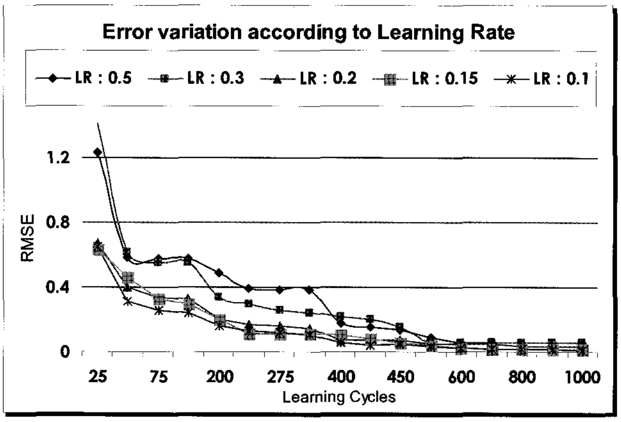


(a) RMSE curves (during 1,000 epochs)

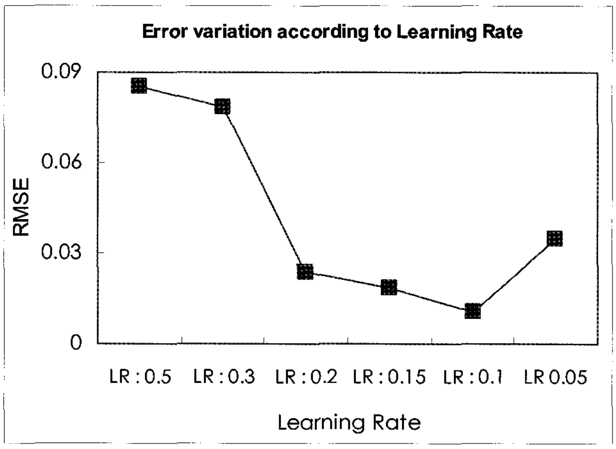


(b) RMSE results after 1,000 epochs

Fig. 6 RMSE results for initial weighted values (0.1, 0.3, 0.5, 0.7, 0.9)



(a) RMSE variation according to learning rate



(b) RMSE result after 1,000 cycles

Fig. 7 RMSE result according to learning rate

4.2 Classification result

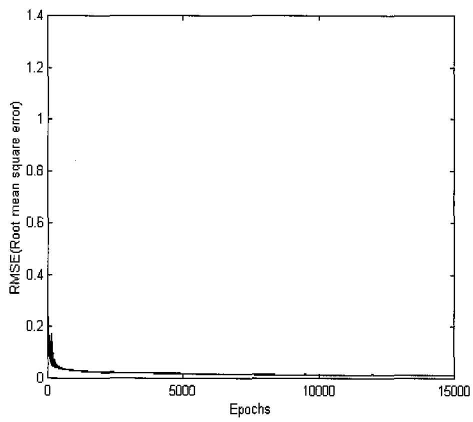
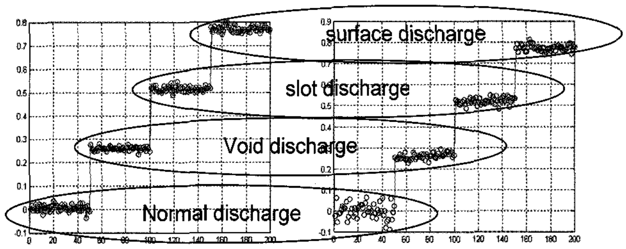


Fig. 8 RMSE result

The pattern of the surface discharge and slot discharge remarkably differed from those of other discharge sources as PD characteristics. This is readily discernible from Fig. 8 and Fig. 9. Fig. 8 shows RMSE (root mean square error) variation value during the processing learning discharge pattern. And Fig. 9 shows training result and classification result between four patterns. During the training process, this output is forced to be equal to '0', '0.3', '0.5' and '0.8' for the cases of normal discharge, internal discharge, slot discharge and surface discharge. Between these total patterns, 50 patterns have been used in the training data, and the remaining 50 patterns have been used in the classification data. At the end of the learning process, the network is successful in discriminating between four different discharge sources of coils with a success rate of 100% in both the training and classification data. As a result of the learning process, the learning capability of the NN with BP is excellent in this case.



(a) training result (b) classification result

Fig. 9 Distribution of PD signal

5. Conclusion

In this paper, PD distribution characteristics are studied as a PD source classification on highly occurring probability defects in the stator coils of traction motors. As a result, we came to the following conclusions.

1. The statistical distribution of PD data is a good tool of discrimination among PD sources.
2. Its success recognition rate becomes 100% using the BP network as a PD classification.
3. NN using the BP technique with input parameter derived from discharge pulse shape is useful in the discrimination of PD patterns.

Acknowledgements

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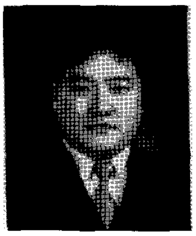

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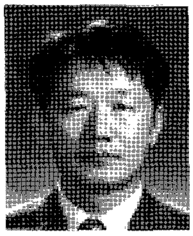

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