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COMMUNICATIONS

Deep convolutional neural networks for automatic coil pitches detection systems in induction motors

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Stator winding structures are one of the most important parameters affecting motor performance in induction motor (IM). When deciding on the coil pitch, the winding structure and the power performance of the motor are also taken into consideration. The stator coil pitch of the IM is known at the design stage of the motor. The stator coil pitch of an IM manufactured and in use may be wanted to be changed with the desire to improve the performance of the motor and suppress some harmonics. In this case, it is necessary to determine the motor winding structure and coil pitch by opening the stator cover of the motor, removing the rotor, and manually examining the stator winding structure visually. However, this process prolongs this improvement process considerably. A system that can detect the stator coil pitch according to the stator current behavior while the motor is running can significantly shorten this improvement process. For this purpose, in this study, a deep convolutional neural network (DCNN) model that can automatically estimate IM stator coil pitch angle with an accuracy rate of 100% is designed and applied.

K e y w o r d s: stator winding structure, stator coil pitch angles, IM, DCNN

1 Introduction

IM are among the most used motors in the industry due to their advantages such as having a simple and dynamic structure and being cheap. IM continue to maintain their popularity for the last thirty years with the advantage of providing easier speed control compared to the past by means of sinusoidal pulse width modulation (SPWM) inverter drives [1]. In industrial applications, IMs are required to operate with maximum efficiency and high performance. The winding structure and coil pitch of IMs are also taken into consideration in the R&D (Research & Development) studies to increase the performance of the IM. Because by changing the IM coil pitch, some single-row harmonics can be suppressed [2]. In addition, the magnetomotive force (MMF) arising from IM windings can be increased with the appropriate winding step. The stator coil pitch angle of an induction machine is determined at the design stage of the machine.

After the motor is produced, the stator windings of the motor are rewound from the very beginning in order to change the motor performance by changing the coil pitch or to make trials for different coil pitchs. In order to interfere with the coil pitch in the development of an IM, it is necessary to know the coil pitch in advance. Being able to be sure how many degrees the coil pitch angle of the IM saves considerable time in motor design and improvement studies. In some cases it is impossible to know the coil pitch angle. It is very difficult to find the coil pitch by mathematical account on induction machines with a deleted or unlabeled. Similarly, in unlabeled motors, in order to know the coil pitch, it is necessary to remove the motor cover or to examine the stator windings by removing the rotor. To shorten this process, automatic bobbin pitch detection systems can speed up research and development activities. The design and implementation of an automatic coil pitch detection system is an issue that is overlooked and neglected.

The original value and motivation of this work is to develop and implement a deep learning algorithm that has not been included in the state of the art until now and, as far as we know, automatically predicts the IM coil pitch angle for the first time. In this study, to solve this problem, a DCNN model is designed and applied for an automatic coil pitch detection system that works according to the instantaneous value of the stator phase currents of identical IM with integer winding structure with different coil pitches. The parts of the study after the introduction and theoretical frame are shaped as follows. In the second part, the aim of the study is explained. In the third part, studies on the subject and the scope of the subject are given. In the fourth part, obtaining the data set and the method used in the study are explained. In the fifth part, the results obtained from the study are presented. In the sixth part, the conclusion and discussion of the study are given.

2 Scope and related works

The active power written on the label of any electric motor is directly related to the length and cross-section of the conductor used in the motor winding. In addition, the coil pitch in the stator winding, the groove shape where the windings are placed, and the position of the windings in the groove are among the parameters that affect the motor. In our previous experimental studies, we emphasized that the coil pitch in IMs affects the total current

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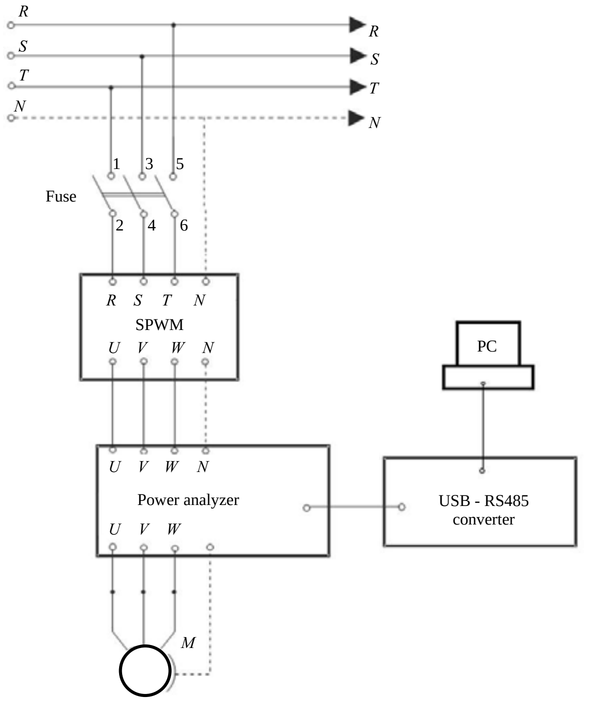

Fig. 1. IM connection diagram for experimental application

harmonics [3, 4], low-level single row current harmonics [5], and total harmonic distortion [6, 7]. In addition to the coil pitch, we emphasized in our scientific and experimental studies that harmonics caused by the semiconductor switching elements in the PWM inverter affect the losses and internal and external temperature of the IM [8], and thus the coil insulation level in the stator windings [9]. In IMs, the groove shape in the stator is also important in terms of stator windings and losses [10 -12].

A study by Hadiocuhe *et al* revealed that the leakage inductance value caused by current harmonics can be reduced when the stator coil pitch is used as a full pitch [13]. In one study, it was found that an IM performs higher when fed with variable PWM switching frequency by shortening the coil pitch in a double layer stator winding [14]. If the stator winding grooves are large enough to allow a second winding to be wound in order to start softly in IMs, in this case, the soft start of the IM can be achieved with parallel winding, and the IM performance can be increased. As an example of this situation, a second winding was wound in the stator cavities in order to a soft start in one study [15]. In some studies, it has been tried to determine the most suitable coil pitch in order to minimize the noise arising due to spatial harmonics in the air gap where the rotating magnetic field between the stator and the rotor is located [16 - 18]. Gundogdu *et al* examined and analyzed in detail the effect of winding structure and coil pitch on IM performance in IMs [19].

In the state of the art, there are also studies to develop stator winding design optimization to suppress MMF harmonic content in the air gap [23-26]. In [23] and [27], it is aimed to attenuate MMF harmonic components through coil pitch abbreviation. It is an important requirement to utilize artificial intelligence, machine learning, or optimization approaches to suppress harmonics through using the optimal winding structure and coil pitch [28].

3 Methodology

3.1 Data set acquisition

The stator windings of the six identical squirrel cage IMs were rewound with different coil pitches, using a conductor of the same cross-section and length so that the label values are maintained. In the study, the experimental application was carried out with IM's with six different coil pitches, respectively, with the largest coil pitch 180 deg (1-10), 160 deg, 140 deg, 120 deg, 100 deg, and the smallest coil pitch being 80 deg. For each coil pitch, the phase current (IL1) value was recorded with a sampling time of 1 second and transferred to the computer by loading IM from unloaded to the overloaded state through the setup in Fig. 1. The IM label value used in the study is shown in Tab. 1.

Table 1. Label values of the IM

Voltage (V)	Frequency (Hz)	Current (A)	Power (kW)	$cos\phi$	Speed (rpm)
Δ 220	50	4.7	1.1	0.80	1380
Y 380	50	2.7	1.1	0.80	1380

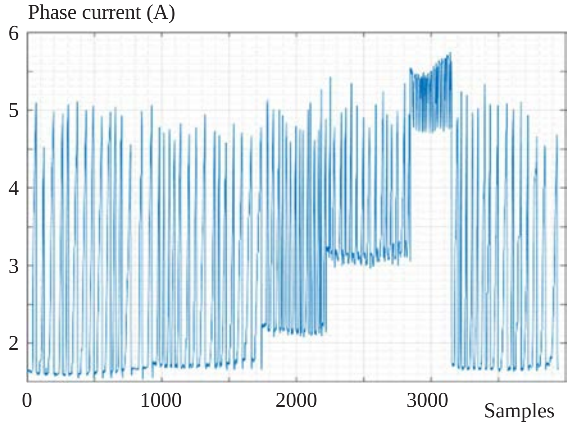

Fig. 2. Phase current graph obtained in each coil pitch

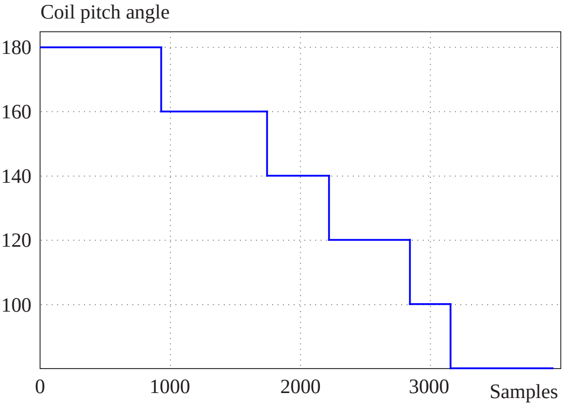

Fig. 3. The coil pitches angles according to the samples

Data was transferred to the computer via the power analyzer shown in Fig. 1 and the RS485 converter. In the study, 3940 sampling points (phase current points) were obtained.

Figure 2 shows the graph of the current values obtained for each coil pitch and Fig. 3 shows the coil pitches according to the samples. The spectrogram equivalent of the same graphic is shown in Fig. 4.

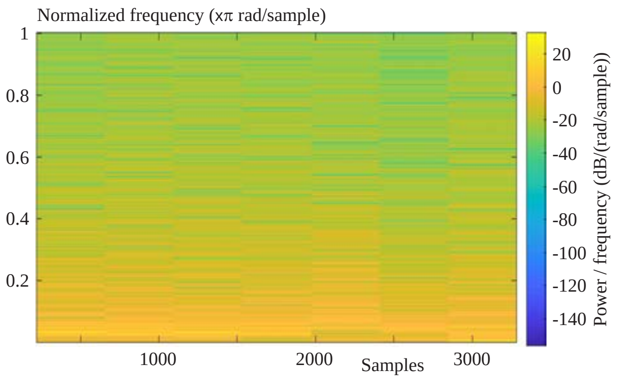

Fig. 4. Spectrogram obtained from IL1 phase current graph

From the spectrogram in Fig. 3, a total of 300 image data, 50 for each coil spacing, were obtained by the data magnification method. In the data augmentation method, frameshift interval was chosen as 5 samples.

3.2 Architecture of the DCNN model

One of the first steps in the design process of a DCNN architecture is to decide on the hyperparameters related to the convolution layer and perform the necessary calculations. In the convolution layer, stride (s) indicates the amount the shifting steps to the left and right, while the matrix $\mathbf{K}$, $(n_{\mathrm{K}} \times n_{\mathrm{K}})$ is a filter matrix to be applied on the $\mathbf{A}$ input matrix $(n_{\mathrm{A}} \times n_{\mathrm{A}})$. The number of rows and columns of the input matrix n_{A} is bigger than or equal to n_{K}. The elements of $\mathbf{B} = \mathbf{A} \bigotimes \mathbf{K}$ matrix, obtained as the output of the convolution process, can be expressed as follows, [20]

$$B_{ij} = \sum_{f=0}^{n_K-1} \sum_{h=0}^{n_K-1} A_{i+f,j+h} K_{i+f,j+h}, \tag{1}$$

the size of the $\mathbf{B}$ matrix is $(n_{\mathrm{B}} \times n_{\mathrm{B}})$, where

$$n_{\mathrm{B}} = \lfloor \frac{n_{\mathrm{A}} + 2p - n_K}{s} + 1 \rfloor \tag{2,}$$

with p - being the padding value.

The next steps after the convolution layer processes are the shaping of the Softmax layer, loss, fully-connected, and classification layers. The Softmax layer is the layer where the cross- entropy loss is calculated and it follows the classification layer. The Softmax layer followed by the last fully connected layer is the output unit activation function used for multiple classifications. For the coil pitches angles classification, the Softmax function for five categories is

$$y_{\mathrm{r}}(x) = \frac{\exp[a_{\mathrm{r}}(x)]}{\sum_{j=1}^{k} \exp[a_j(x)]}. \tag{3}$$

For the probability distribution of multi-class classification; $0 \leq y_{\mathrm{r}} \leq 1$ and $\sum_1^k$ indicates the conditional probability of the sample in class r.

In this study, the architecture of the pre-trained ResNet-18 model [21] and the MATLAB environment were re-edited and used for coil pitch angle detection and classification. In this study, the architecture of the pre-trained ResNet-18 model [21] was re-edited for coil pitch prediction in the MATLAB environment by transfer learning approach. Transfer learning is a machine learning technique that allows some layers or functions of a DCNN trained for a specific task to be developed again for a new task. In the ResNet-18 architecture, the rectified linear unit (ReLU) activation function is connected after each convolution layer. The ResNet-18 model consists of 2 pooling layers, 17 ReLu layers, 20 convolution layers, and 20 normalization layers.

We reconsidered the pre-trained ResNet-18 architecture by using the "transfer learning" technique. The ResNet-18 architecture was designed to classify 1000s and was trained with more than one million data. We rearranged the last three layers (fully connected, Softmax and classification) to make a 6-class classification to determine the coil pitch angle of this model. We did not change the learning rate of the previous layers exclusive to the last three layers but increased the learning rate of the new layers a little more than in the original so that they adapt faster to the new situation.

3.3 Training and testing the DCNN model

The study was carried out with NVIDIA GeForce GTX 1650, 8055 MB GPU laptop. Training and testing of the DCNN model took 1 minute 18 seconds. Table 2 shows the hyperparameters selected for training and testing of the DCNN model.

Table 2. Limitations for the training and validation process

Hyperparameters	Values
Max. epoch	30
Max. iteration	120
Validation Frequency	5
Initial learning rate	0.001
Minibatch size	50
Learning rate schedule	constant

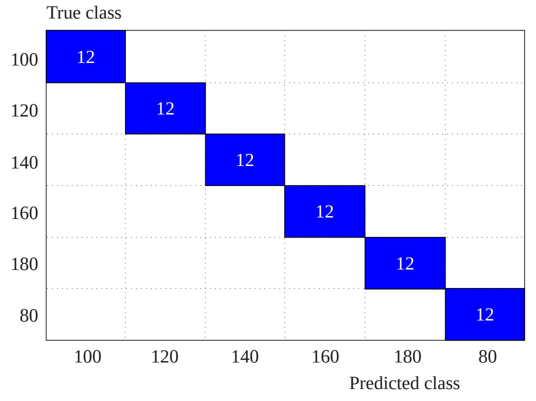

Fig. 5. The confusion matrix obtained from testing of the DCNN model

In the training duration of the DCNN, the input from the Softmax layer in the classification layer is assigned to one of the K classes that mutually excluded through the cross-entropy function. Training of the DCNN network continues until the loss function is minimized. In (4) the loss function, N is the sample number, K is class number, t_{ij} is the output for j class i sample, and y_{ij} is output for j class i sample [22].

$$Loss = -\sum_{i=1}^{N}\sum_{j=1}^{K} t_{ij} \ln y_{ij} . \tag{4}$$

4 Results

As a result of training and testing the DCNN model, the test result with 5-fold cross-validation can be observed in Tab. 3 according to the 120-th iteration and 30-th Epoch. According to this table, 100% accuracy has been achieved. According to Fig. 5 confusion matrix, the 12 images used as test data for each coil pitch were all estimated at 100% accuracy. Figure 6 shows the accuracy rate and error curves obtained as a result of the test and training process.

5 Conclusion

It is a fact that DCNN algorithms are not much preferred for electrical machines, as they require two-dimensional data such as image data. However, in this study, by using DCNN effectively, it proved to be a preferable method in electric motor design. With the pre-trained DCNN model using the transfer learning technique, the coil pitch angles of an IM could be predicted with 100% accuracy. The reliability of the model has been strengthened by the test results made with 5-fold cross-validation. It was concluded that many deep learning methods can be used in the selection of the most optimal coil pitch in IM, as well as the DCNN method is very useful and produces satisfactory estimation and classification results.

Table 3. Testing and training processes summary of the DCNN model

Iteration	Epoch	Time Elapsed (mm:ss)	Training Accuracy (%)	Testing Accuracy (%)	Training Loss	Testing Loss
1	1	00:10	24	25	2.9369	2.8908
5	2	00:13	78	80	0.9238	0.8762
10	3	00:16	100	97	0.1076	0.2462
15	4	00:19	96	98	0.1271	0.1594
40	10	00:33	100	100	0.0057	0.0209
85	22	00:58	100	100	0.0023	0.0120
105	27	01:10	100	100	0.0020	0.0111
120	30	01:18	100	100	0.0019	0.0106

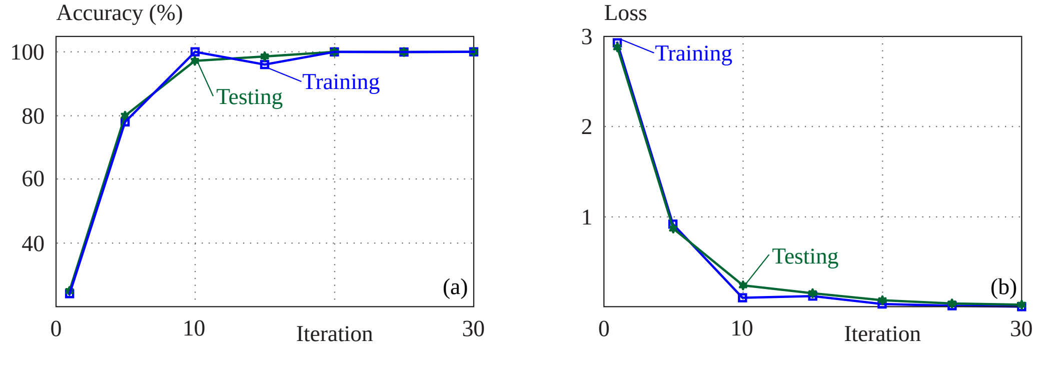

Fig. 6. Accuracy and loss curves of the DCNN model for training and testing (a) – accuracy curves, (b) – loss curves

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