Power Electronics and Drives
Volume 9(44), 2024 DOI: 10.2478/pead-2024-0002

Analysis of PMSM Short-Circuit Detection Systems Using Transfer Learning of Deep Convolutional Networks

Research paper

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Received: 29 October, 2023; Accepted: 8 December, 2023

Abstract: Modern permanent magnet synchronous motor (PMSM) diagnostic systems are now combined with advanced artificial intelligence techniques, such as deep neural networks. However, the design of such systems is mainly focussed on a selected type of damage or motor type with a limited range of rated parameters. The application of the idea of transfer learning (TL) allows the fully automatic extraction of universal fault symptoms, which can be used for various diagnostic tasks. In the research, the possibility of using the TL idea in the implementation of PMSM stator windings fault-detection systems was considered. The method is based on the characteristic symptoms of stator defects determined for another type of motor or mathematical model in the target diagnostic application of PMSM. This paper presents a comparison of PMSM motor inter-turn short circuit fault detection systems using TL of a deep convolutional network. Due to the use of direct phase current signal analysis by the convolutional neural network (CNN), it was possible to ensure high accuracy of fault detection with simultaneously short reaction time to occurring fault. The technique used was based on the use of a weight coefficient matrix of a pre-trained structure, the adaptation of which was carried out for different sources of diagnostic information.

Keywords: *transfer learning • motor fault detection • inter-turn short circuits • convolutional neural network • field-circuit PMSM model*

1. Introduction

The dynamic development of artificial intelligence methods has contributed to many changes in the technique of diagnostic tests carried out within AC motors. For many years, shallow neural networks in the form of multilayer perceptron (Moosavi et al., 2015; Sá et al., 2019), self-organising Kohonen maps (Chuang et al., 2017; Skowron et al., 2023), networks with radial activation functions (Önel et al., 2006; Pietrowski, 2011; Puhan and Behera, 2017), or recurrent structures (Asfani et al., 2012; Gao and Ovaska, 2002) were mostly used. The shallow neural structures solved the problem of assessing membership in one of the declared classes (categories or degree of defect). Therefore, it was necessary to develop input vectors of the network that carry information about the technical condition of the machine tested. The stage of symptom extraction resulted in a lack of complete automatisation of the diagnostic system-implementation process because it was based on empirical knowledge. Furthermore, the determination of damage symptoms in the vast majority of cases involved the use of signal-processing methods. The use of techniques for processing quantities measured in the time domain, frequency domain (Moosavi et al., 2015; Skowron et al., 2023), or higher-order analyses (Bracale et al., 2007; Pietrzak and Wolkiewicz, 2022; Rosero et al., 2009) resulted in several limitations of the designed diagnostic system. The first limitation is the long signal acquisition time relative to the dynamics of the defect progression, which is particularly important in defects of an electrical nature (inter-turn short circuits). Unfortunately, the long measurement time is necessary to ensure

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high-quality diagnostic information (spectrum resolution). Another limitation is the inability to detect defects in transients (changes in machine operating conditions) encountered with basic Fourier analysis. Analysis of transient states using time-frequency techniques results in a significant increase in computational time, which ultimately increases the response time of the system to an emerging fault. An additional limitation of the classical approach to the implementation of neural structures in diagnosis is the need for an expert in the stage of extraction of damage symptoms.

The solution to the limitations mentioned above is the direct processing of diagnostic signals via deep neural structures, which has been used in recent years (Chen et al., 2019; Guo et al., 2016; Kao et al., 2019; Li et al., 2018; Skowron et al., 2022). The idea of deep learning is to depart partially from the principle of universal approximation and to significantly increase the number of neural connections. Furthermore, the use of extensive learning data packages and stochastic training methods allows the network structure to automatically extract damage symptoms (Ding and He, 2017; Skowron et al., 2021). Consequently, deep networks allow us to omit the stage of extracting damaged features. On the other hand, the use of direct processing of diagnostic information (measured signal) results in multiple reduction of the response time to occurring damage, as demonstrated by Ince et al. (2016) and Skowron et al. (2022), among others. The main representative of deep networks in machine diagnostics is the convolutional neural network (CNN). CNNs are used in both electrical and mechanical defect detection (Chen et al., 2019), as well as demagnetization (Skowron, 2023). The structure of the CNN provides a high level of precision in the detection of defects in the steady-state and transient states. An unquestionable advantage of CNNs is the extremely short reaction time to occurring damage amounting to tenths of a second (Skowron and Kowalski, 2022; Skowron et al., 2021). However, despite the advantages mentioned above, deep structure systems require a long training time (adaptation of weight factors), which makes implementing new diagnostic application functions much more difficult.

An extension of well-known deep learning methods that enable system expansion using existing structures is the transfer learning (TL) technique (Chen et al., 2020; Guo et al., 2019; Qian et al., 2018; Wu et al., 2020; Xu et al., 2020). The idea of TL is to use a neural structure trained for one task in a different but similar classification problem (Xiao et al., 2019; Yan et al., 2020; Yang et al., 2019). Diagnostic systems using TL are characterised by high precision performance for both convolutional structures (Lu et al., 2020; Skowron, 2023) and autoencoders (Wen et al., 2019). The technique provides the opportunity to develop universal detection systems for different machines, as well as to fully exploit knowledge derived from mathematical models. Furthermore, TL provides a clear reduction in the implementation time of diagnostic systems while maintaining the high precision of deep neural structures (Skowron, 2023).

This article presents the results of a study on the application of CNN TL in a diagnostic system for permanent magnet synchronous motor (PMSM) stator windings. The presented applications use two different sources of diagnostic information: the measured phase current of the induction motor and phase current signals from the field-circuit model of the PMSM. The idea of the presented method is to make full use of a fragment of the structure (weighting factors of the convolution layer) of a network trained for another classification problem. The technique is successfully applied to diagnostic applications of electric motors (Chen et al., 2020; He et al., 2020; Shao et al., 2019; Skowron, 2023). To show the advantages of the proposed idea, the transfer of information between the model and the real object (PMSM) was applied, as well as the use of information from measurements on the induction motor (IM) in PMSM diagnostics.

The article is divided into three sections. The first section discusses the idea of TL techniques applied to the PMSM stator winding diagnostic system. The section includes a description of the structure of the convolutional network, the development of training data packets, and the CNN training process according to the idea of TL. The second section presents experimental verification of the described diagnostic systems based on information from the mathematical model and measurements of the induction motor. This section includes a comparison of the two systems in terms of the effectiveness of PMSM inter-turn short circuits detection. The article concludes with a summary of the research results and a presentation of further planned research work on the development of the idea of TL in the field of machine diagnostics.

2. The Idea of TL of Deep Convolutional Networks

TL of deep neural networks is a relatively new approach to machine learning, which is based on the full use of the knowledge gained by a neural network in solving one problem and subsequent use of this knowledge in a different but similar domain task. This method ensures the achievement of much better classification results without the need to redesign the neural structure while speeding up the process of training the network; thus, it introduces savings in the computational resources of the host system. It should be clearly emphasised that TL will maintain high efficiency when the learned representations and data structures are well generalised, while the domains of both tasks (source and target) are related. This requirement is ensured when TL is applied in the field of electrical machine diagnostics.

The CNN TL technique used in the study, termed 'neural network-based TL', was based on the use of a fragment of a pre-trained neural structure in the target structure (PMSM diagnostic system). This approach makes it possible to use the automatic feature extraction capability of the input matrix to solve a new multi-criteria classification problem (damage assessment). The study presents a comparison of two developed PMSM stator winding diagnostic systems using direct processing of the signal measured by a CNN. The CNN training process was carried out according to the idea of TL to use information from the field-circuit model of the PMSM and measurements on the real object (squirrel-cage induction motor). The conceptual diagram of the applied convolutional network learning technique is shown in Figure 1.

Figure 1 presents the idea of TL depending on the source of diagnostic information:

- Model–Object: PMSM motor diagnostic application developed based on features preserved in the phase current signals from the PMSM field-circuit model.
- Object–Object: PMSM motor diagnostic application developed based on information preserved in the measured phase currents of a squirrel-cage induction motor.

Accordingly, the possibility of switching from a mathematical model to a real object was analysed, as well as using a detection system developed for another object. Nevertheless, the implementation of the target system for both cases proceeded analogously.

The first stage of implementing the TL technique was the classic process of training the convolutional network (Figure 1—marked as **(1)**). The adaptation process aimed to determine the source structures of the convolutional network, the knowledge of which was acquired for other diagnostic tasks (for objects other than the target one). The parameters of the neural structures used for the two diagnostic systems are presented in Table 1. The adaptation of the weight coefficients of the convolutional layers was carried out according to the stochastic gradient descent

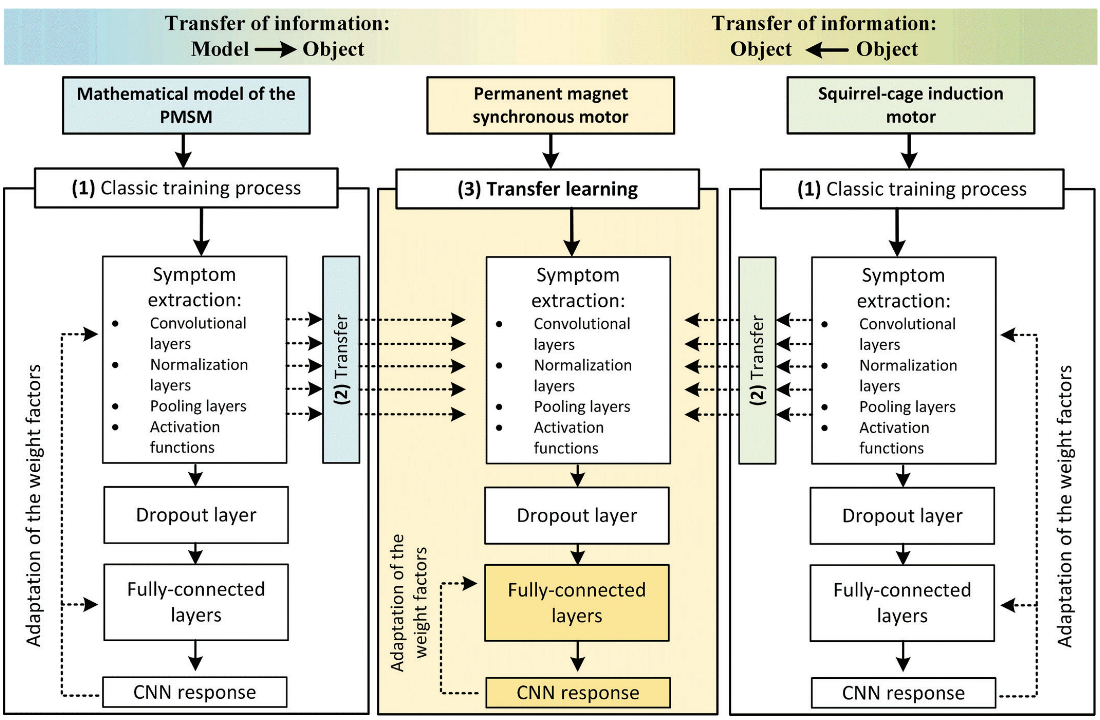

Fig. 1. Idea diagram of the applied CNN TL technique. CNN, convolutional neural network.

Name of parameter	Model>>Object Value	Object>>Object Value
Number of convolutional layers	3	4
Number of filters in particular layers	30 – 20 – 10	40 – 0 – 30 – 20
Depth	3	–3
Number of pooling layer	3	4
Pooling method	Maximum	Maximum
Pool size	3 × 3	3 × 3
Stride	2 × 2	2 × 2
Activation function	ReLU	ReLU
Number of fully connected layers	3	2
Number of fully connected neurons	20 – 10 – 4	20 – 4

CNN, convolutional neural network.

Table 1. Parameters of the CNN structures used in the studies.

with the momentum (SGDM) algorithm. The research used a stochastic training method based on mini-data packets consisting of randomly selected samples from the entire training set. The size of the mini-package was determined in such a way that all cases from the training set were presented in a given epoch. The parameters of the training process according to the SGDM algorithm are listed in Table 2. It should be clearly emphasised that in the first stage of training, the network layers responsible for the automatic extraction of symptoms from the input matrix (convolutional layers) and the classifier layers responsible for determining belonging to one of the categories (degree of damage) were adopted.

After completing the training process of CNN structures constituting the basis of the source system, the second stage of TL implementation begins (Figure 1—marked as **(2)**). At this stage, the weighting coefficients of the convolutional layers of the source structure are locked ('frozen') and are not subject to further adaptation. Owing to this, the features acquired during the training process (symptoms of damage) are transferred to the target structure (Figure 1—'Transfer'). The further training process includes turning off the classifier layer (marked in yellow in Figure 1), i.e. the structure of the multilayer perceptron. In this way, the second stage of training uses the ability to recognise damage patterns (Figure 1—marked as **(3)**). TL gives CNNs the ability to combine well-known features of the input matrix to solve a new problem. The need to re-select the network structure and parameters of the training process, which is limited only to the perceptron, is eliminated. Therefore, the implementation of new functions is very simple because it depends only on the simplest perceptron structure. It should be clearly emphasised that currently there are no specific formal rules for selecting the parameters of deep structures. The research used techniques for selecting hyperparameters of the structure and training process, developed on the basis of previous research work. The use of the presented idea of TL of a deep convolutional network enabled the development of two PMSM diagnostic systems.

2.1. Implementation of the structure and training process of the convolutional network

A characteristic feature of deep neural structures is the need to develop a comprehensive training data package to ensure that the network acquires the ability to automatically extract features. Furthermore, each of the sample networks presented should provide sufficient information about the technical status of the tested object. Due to the automatic extraction of symptoms by convolutional layers, the research did not use methods for processing the measured values. The proposed diagnostic systems were based on the use of only 500 samples of the phase current signal in 3 phases of the PMSM stator. Assuming a sampling frequency of 8,192 Hz, the measurement acquisition time was approximately 0.061 s. Therefore, even a few seconds of measurement of diagnostic signals ensures the processing of a large data package. Therefore, from the point of view of data acquisition time, the development of classical methods based on signal analysis does not differ significantly from the development of input vectors for a deep network. When using classic spectral analysis, a 10-s measurement ensures the development of one training sample. However, in the case of CNN direct processing, a 10-s measurement provides information on nearly 160 cases. A schematic diagram of the method used to develop CNN input matrices is shown in Figure 2.

The data acquisition system was developed in the LabVIEW environment from National Instruments, while the analysis of data packages, the selection of neural structures, and the learning process were implemented in the MATLAB environment. Data acquisition was carried out using two experimental setups with an induction motor and a PMSM with a power of 3.0 kW and 2.5 kW, respectively (Figure 3). The special design of the machines enabled

Name of parameter	Value
Learning method	Stochastic gradient descent with momentum
Momentum coefficient	0.95
Initial learning rate	0.012
Number of learning epochs	1,000
Execution environment	GPU
Drop period	30 epochs
Validation frequency	Every 50 iterations
Shuffle method	Every epoch
Mini-batch size	90
Name of parameter	Value

Table 2. Parameters of the SGDM training process used in the studies.

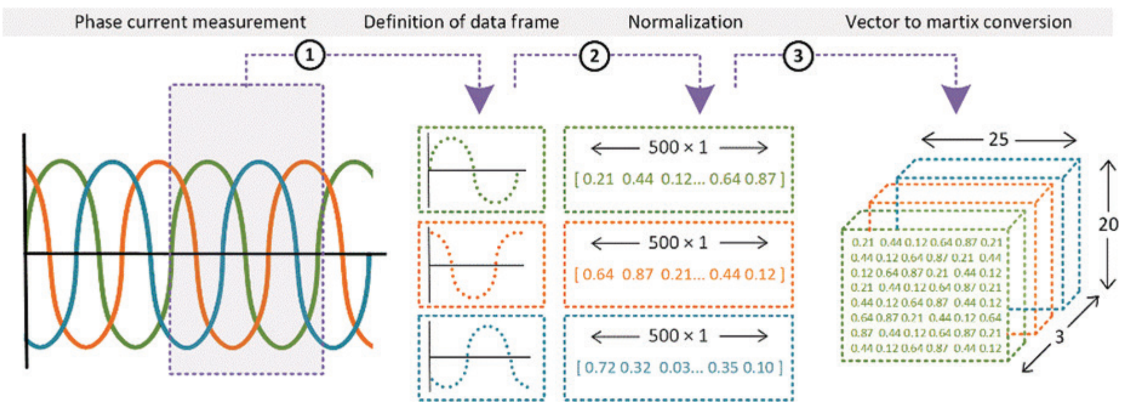

Fig. 2. Development of CNN input matrix—idea scheme. CNN, convolutional neural network.

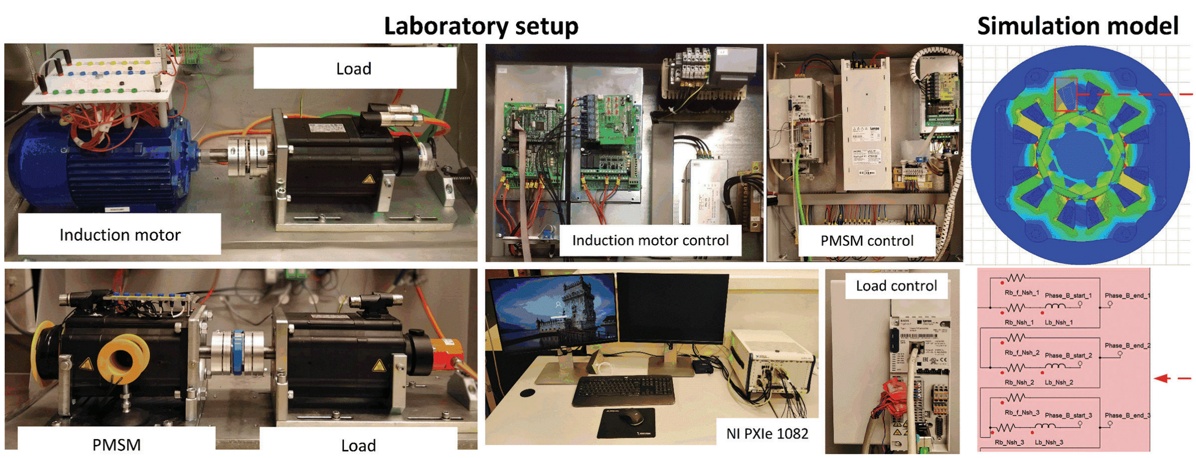

Fig. 3. Development of CNN input information: experimental setup (induction motor, PMSM); simulation model. CNN, convolutional neural network; PMSM, permanent magnet synchronous motor.

Name of parameter	Induction motor	PMSM	Unit	Symbol
Power	3,000	2,500	W	P_N
Torque	19.83	16	Nm	T_N
Speed	1,445	1,500	r/min	n_N
Stator phase voltage	400	325	V	U_{sN}
Stator current	6.8	6.6	A	I_{sN}
Frequency	50	100	Hz	f_{sN}
Pole pairs number	2	4	–	p_p
Number of stator winding turns	480	750	–	N_s

PMSM, permanent magnet synchronous motor.

Table 3. Rated parameters of tested motors.

physical modelling of damage to the stator windings (inter-turn short circuits). The research was limited to the analysis of defects in the range of 0–3 short turns in a single stator phase (N_{sh} = 0–3). To analyse the impact of the load torque on the stator fault detection process, the machines were mechanically coupled with PMSM motors acting as a load. The diagnostic information used in the system based on the PMSM model was obtained as a result of simulations carried out using the Ansys Maxwell environment (Figure 3). Simulation tests were carried out in the same range of load torque changes. Due to the high precision of the simulation related to the calculation step, current data was collected at a frequency analogous to that used in experimental studies (8,192 Hz). Owing to this, it was possible to determine the actual usefulness of the information from the field-circuit model in the diagnostic method presented. The parameters of the electrical machines used in the research are listed in Table 3.

Based on the phase current measurements, network input matrices with dimensions of 25 × 20 × 3 were developed, where the third dimension of the matrix corresponds to the number of diagnostic signals (three phase currents). Each data package contained samples obtained for the four technical states of the analysed stator coils N_{sh} = 0, 1, 2, 3) and the variable operating conditions of the tested machine (T_L = 0-T_{LN} with a step of 0.2 T_{LN}; f_s = 10–50 Hz for an induction motor; f_s = 50–100 Hz for PMSM). Furthermore, validation sets different from the training ones were developed and used in the analysis of the training process. The validation sets allowed us to observe the course of the learning curves for unknown samples during the training process. Owing to this, it was possible to appropriately select the parameters of the training process (learning rate, momentum factor) while eliminating the risk of losing the generalisation ability of the CNN. Additionally, to verify the accuracy of the training process, a testing package was developed and used after the training process. This package also included samples for transient states (changes in load torque), which enabled confirmation of the generalisation ability of the CNN. The list of data packages developed for the objects analysed (induction motor, PMSM model, PMSM) is presented in Table 4.

2.2. Neural network-training process

The training process was performed according to the stochastic gradient descent with momentum (SGDM) algorithm for 1,000 training epochs with an initial learning rate of 0.012. The momentum coefficient was set at 0.95 (Table 2). According to the SGDM algorithm, the adaptation of weighting factors was based on mini-packets containing randomly selected samples from the training data set. The idea of SGDM assumes that the gradient is an expected value that can be approximated using a small data set. At each step, a mini-package of examples from the training set is sampled. The packet size was set at 2% of the total training set size, based on previous research results on the use of CNNs in machine diagnostics. The course of the learning curves of the proposed diagnostic systems for the validation data is shown in Figure 4 (CNN precision for the classification task—Figure 4a, and the value of the loss function—Figure 4b).

The analysis of learning curves allows us to observe higher dynamics of the training process based on information from the PMSM model (Model>>Object) than in the case of using data from measurements on the induction motor (Object>>Object). However, despite the initial differences in the level of precision obtained in the first epochs of training (Figure 4a), the final precision for both systems is at a very similar level. It should be clearly emphasised that the process in both cases was convergent, which is an advantage considering the differences between training and validation packages. The convolutional layer training was performed on objects other than the target PMSM.

Name of parameter	Induction motor	PMSM model	PMSM
Training data	5,760	6,000	5,400
Validation data	5,760	6,000	5,400
Testing data	5,760	6,000	5,400

PMSM, permanent magnet synchronous motor.

Table 4. Size of data packets used in the studies.

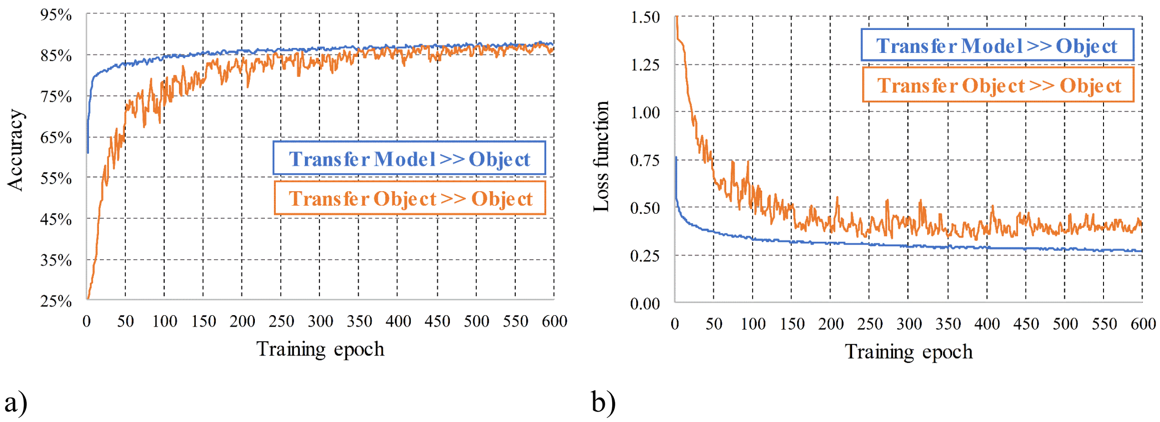

Fig. 4. Convolutional network-training process: (a) classification precision, (b) loss function for validation data.

Therefore, the features of the input matrix determined by CNN in the first stage of TL are, to some extent, universal. Therefore, the fault symptoms developed for the model and the induction motor can be used successfully in the PMSM diagnostic system. However, the observation of the loss function (Figure 4b) allows us to notice that the transfer between the induction motor and the PMSM (Object>>Object) is characterised by a high level of oscillation of the learning curves compared to the transfer between the model and the PMSM (Model>>Object). This fact is related to the initial determination of the classifier's weight coefficients after switching to another object. The phenomenon of curve oscillations disappears as the CNN learning process progresses (Figure 4). It should be noted that the transfer of knowledge between objects with different structures (induction motor and PMSM) is a much more difficult task than the transfer from the PMSM model to the real object. This is due, among other things, to the large impact of the rotor with permanent magnets on the PMSM phase current, especially observed at low rotational speeds and low load torque. The interference of the rotor results in significant difficulties in the process of detecting short circuits in the stator windings in the initial stage of this defect. This problem does not occur in the induction motor, so the transition from this object to the PMSM requires an appropriate selection of the weighting factors of the classifier layer. Prolonged adaptation and oscillations resulting from the above-mentioned differences are observable in the learning curves (Figure 4).

3. Experimental Verification of Diagnostic Applications

3.1. Analysis of the detection system operation during transients

After completion of the CNN training process, the experimental verification of the developed PMSM stator winding diagnostic systems was carried out. The assessment of the precision of the applications was analysed during the operation of the drive system with the PMSM. The verification consisted of modelling the instantaneous short circuit of 3 turns of phase B of the PMSM stator during load torque changes in the range of 0-T_L with a step of 0.2 T_{LN}. The inter-turn short circuits were made in the form of a metallic connection. The test results of the proposed fault detection

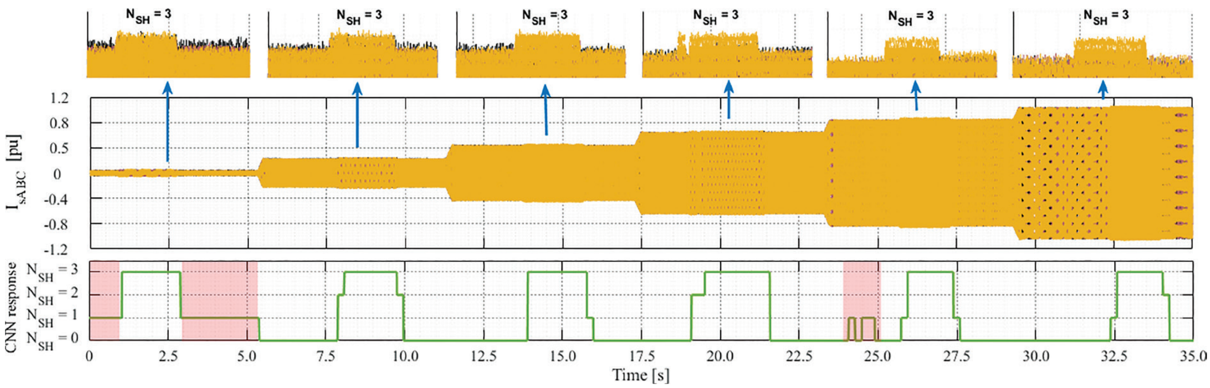

Fig. 5. Experimental verification of the PMSM stator winding diagnostic system: response of the system using the transfer of information from the model to the object, f_s = 100 Hz, T_L = var. PMSM, permanent magnet synchronous motor.

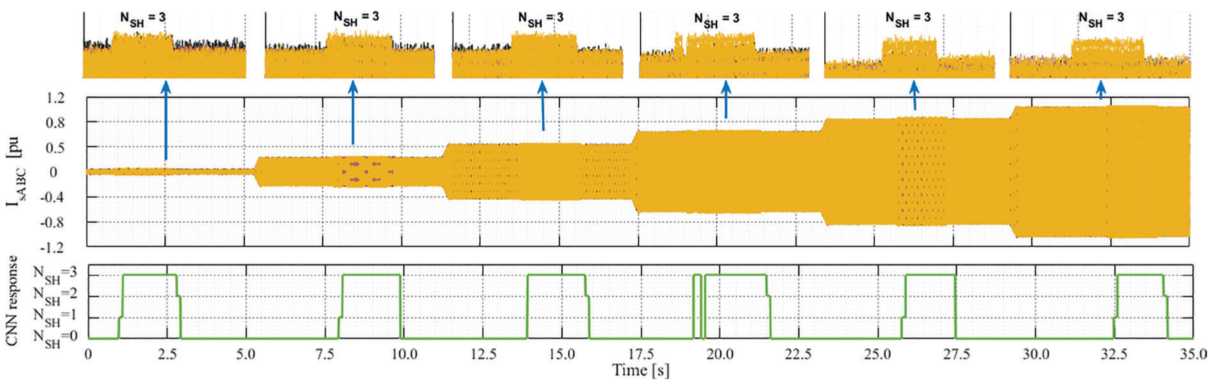

Fig. 6. Experimental verification of the PMSM stator winding diagnostic system: response of the system using the transfer of information from the object to the object, f_s = 100 Hz, T_L = var. PMSM, permanent magnet synchronous motor.

techniques for the rated rotational speed are presented for the systems (Model>>Object) and (Object>>Object) in Figures 5 and 6, respectively.

The analysis of the experimental results shown in Figures 5 and 6 confirms the effectiveness of the proposed diagnostic approach. Diagnostic systems developed are characterised by very high precision in assessing the technical condition of the machine, both in steady and transient states. Moreover, the dynamic change of the load torque does not affect the CNN response. This is a big advantage, especially considering the use of direct analysis of phase currents by CNN. Changing the load torque directly affects the change in the amplitude of phase currents. Therefore, systems using direct processing of these diagnostic signals must be characterised by high generalisation ability. Only then is it possible to correctly distinguish between the change in load torque and a short circuit in the stator windings. From a practical point of view, modern drive systems are characterised by very high dynamics of changes in operating conditions (load torque). Therefore, the proposed approach is a very good diagnostic solution, especially during transient states in which classical signal-processing methods cannot be used. Moreover, the analysis of the system's response to the occurring short circuit of 3 turns of phase B allowed us to observe higher dynamics of the system based on information from the model (Model>>Object). The average reaction times to the occurring faults were 0.071 s and 0.092 s for the (Model>>Object) and (Object>>Object) systems, respectively. In the case of assessing the degree of defect (classification), a faster response of the diagnostic application was also observed based on the information from the model. Moreover, the test results presented in Figures 5 and 7 allow us to observe a clear influence of the rotor's permanent magnets on the process of detecting winding short circuits at no load (Figure 7—network responses marked in red) in the case of model-based diagnostic applications.

As shown in Figure 7, the system based on the transfer of information from the model to the object provides incorrect information when operating without load. The condition of a single shorted turn in phase B is incorrectly

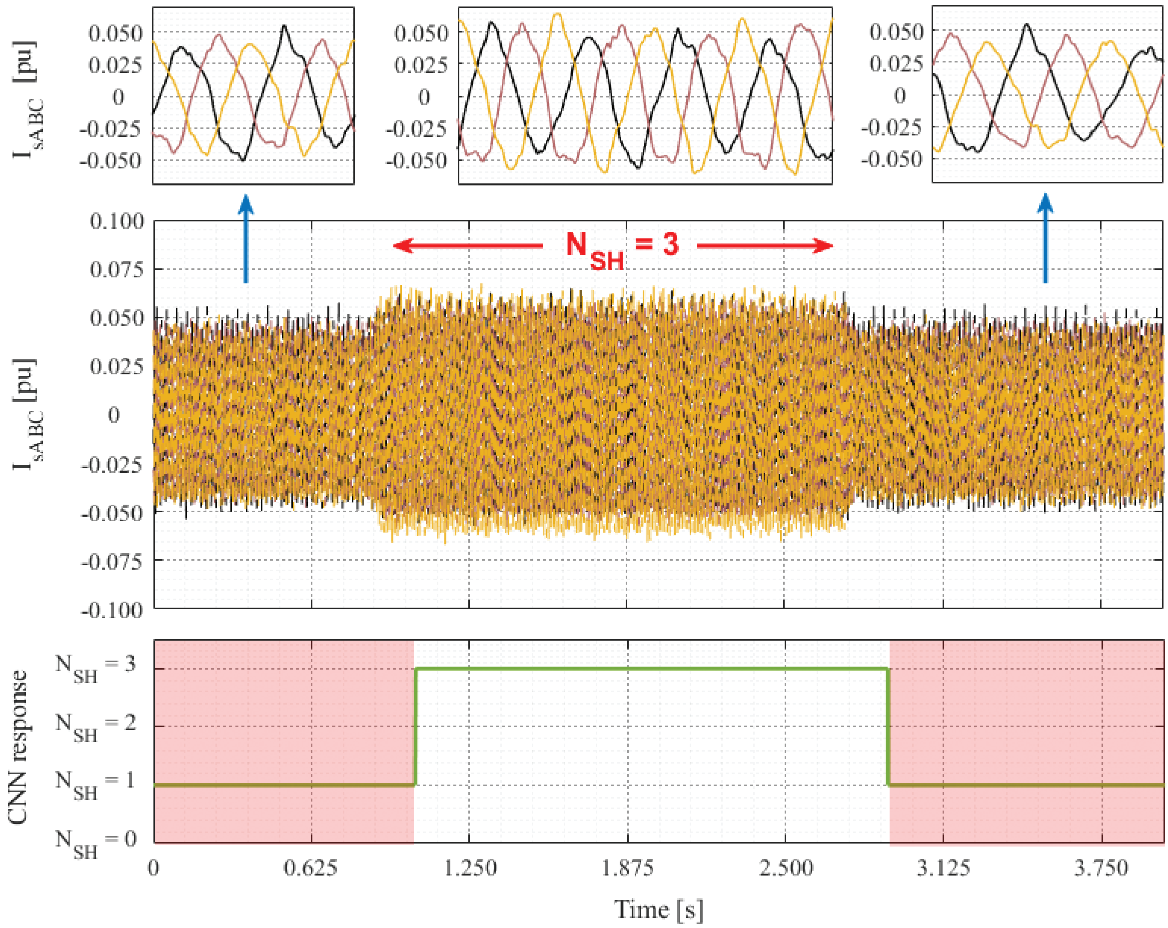

Fig. 7. Experimental verification of the PMSM stator winding diagnostic system: response of the system using the transfer of information from the model to the object, f_s = 100 Hz, $T_L \approx 0$. PMSM, permanent magnet synchronous motor.

detected despite the actual absence of this fault. A detailed analysis of the network operation allowed us to notice that this phenomenon is the result of the influence of the rotor's permanent magnets on the stator current during no-load operation, which is visible in the current waveforms shown in Figure 7. The oscillations that appear then constitute a disturbance to the CNN structure trained on the mathematical model where such current fluctuations do not occur.

3.2. Comparison of PMSM stator winding diagnostic systems based on CNN TL

The analysis of two proposed PMSM stator winding damage-detection systems using the TL technique allowed us to observe that the proposed approach is characterised by a very high level of precision. The detection efficiency determined for steady states was more than 95% and 99% for systems based on information from the field-circuit model (Model>>Object) and the induction motor (Object>>Object), respectively. A slightly lower level of precision was determined for the classification task, understood as the assessment of the exact degree of damage (Table 5). The indicators presented in Table 5 were based on the system response to 5,400 cases. Detection efficiency includes damage recognition (two categories), while classification efficiency determines the ability of the CNN to recognise the exact degree of damage (multi-criteria classification). The analysed cases included various degrees of damage to the stator windings and variable machine operating conditions. The results obtained confirm the higher precision of detection and classification of the system using the transfer of features from the system dedicated to the induction motor to PMSM (Object>>Object). However, considering that the key task of diagnostic systems is to detect damage, the lower precision of the degree assessment obtained does not

Assessment criterion	Model>>Object	Object>>Object
Fault detection time (s)	0.071	0.092
Fault classification time (s)	0.083	0.102
Detection precision (%)	95.02	99.15
Classification accuracy (%)	94.31	96.93
Number of neuronal connections	9,040	27,060

PMSM, permanent magnet synchronous motor.

Table 5. Comparison of PMSM winding fault-detection systems.

negatively affect the evaluation of the proposed approach. The analysis of the research results in transient states allowed us to observe differences in the reaction times of neural structures to emerging damage. The system using information from the PMSM model (Model>>Object) was characterised by an average response time to emerging damage that was approximately 0.02 s shorter. This difference is due to the higher number of neural connections in the system (Object>>Object), which ensures a high level of precision (Table 5). However, as shown in Figure 5, the system based on the transfer of information from the model to the object (Model>>Object) provides incorrect information when operating without load. However, a comparative analysis of the responses of the diagnostic systems shown in Figure 7 allows us to notice that despite the slower response to emerging damage, the system based on the transfer of information between objects is characterised by a very high level of precision. Due to the use of data from another object (induction motor), the training process was extended and resulted in a higher generalisation ability of the CNN. To finally compare the proposed approaches, Table 5 provides the summary results of experimental studies.

The analysis of the proposed diagnostic approach based on TL, due to its high precision, can provide an alternative to current AC motor diagnostic applications. Diagnostic systems for electrical machines using artificial neural networks used to date can be divided according to the source of information of the faults analysed. Most often, the damage characteristic information is the result of measurements on a specially crafted motor enabling physical damage modelling. In this system, the neural network is trained for a data package developed for the physical model and verified on the target object without tuning the network parameters. Unfortunately, this method is limited to only one damage type and one machine type. This fact is due to the impossibility of defining universal features of equal levels for different machines. Unfortunately, this idea additionally excludes cognition of the initial stage of damage and in many cases is not practically feasible due to the dangers involved (inter-turn short circuits in high-power motors).

The solution to the physical damage modelling problem is to use a mathematical model of the machine under investigation. The process of training the neural structure is based on information from the model, while verification is carried out on the real object. This approach has the advantage of identifying damage symptoms without damaging the machine. However, these systems are subject to error due to simplifying assumptions made when designing mathematical models of machines. In addition, the lack of interference from measurement noise, mechanical imperfections, and magnetic imperfections in real machines does not allow for high-precision detection systems. It should be clearly emphasised that the classical approach assumes the necessity of redesigning the network structure, selecting the parameters of the training process and carrying out the learning process each time the task is changed (type of damage, type of machine) or the scope of the network is extended (change in the number of damage categories recognised).

The approaches presented in the article are distinguished by the complete omission of the neural network design process when changing the task or expanding the scope of the diagnostic system. The developed systems were characterised by high precision, short response time to emerging fault, and, above all, simplicity of the process of training a deep network when changing the task posed to the network. This fact is of particular importance in the context of deep learning, characterised by the lack of formal rules for parameter selection and network hyperparameters. The use of deep learning enables the development of universal fault symptoms that can be used in the further development of the diagnostic application. It is also important to make full use of the information from the mathematical model so that a change in defect type does not require the development of a physical model of the object to generate patterns. In addition, the developed approach requires the exclusion of training a small fully connected layer structure to adapt the weighting factors.

4. Conclusions

The use of the idea of TL allows for a significant expansion of the scope of analysed damages while maintaining high efficiency of their detection and classification. Based on the results of the research presented, it can be concluded that it is possible to use defect symptoms (damage features) developed for an induction motor in PMSM diagnostic tasks. Research also demonstrated the ability to fully use information from the PMSM model to determine diagnostic patterns. Moreover, the use of the mathematical model presented in the article does not require physical modelling of damage, which is particularly important in the case of the analysis of high-power motors. However, model-based systems do not provide high precision when operating the drive with low load torque. In the absence of load, the interaction of the rotor with permanent magnets introduces disturbances in the current waveforms, causing incorrect diagnostic information to appear at the output of the system based on information from the PMSM field-circuit model. This problem is not observable when information is transferred between an induction motor and a PMSM. Due to the above, the idea of TL can be successfully used in PMSM diagnostic systems when the source of information is a mathematical model (for the machine's operation under load) and an induction motor (in the full operating range). Moreover, the idea of TL eliminates the difficulties in selecting the hyperparameters of the CNN structure and the training process. The diagnostic systems presented in the article were characterised not only by very high precision in the detection and classification of PMSM stator faults, but also by limiting the duration of the diagnostic signal measurement by using direct processing of phase currents.

Acknowledgements

This research was supported by the National Science Centre Poland under grant number 2021/41/N/ST7/01673.

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