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***Abstract*—The paper deals with description, design, learning and inference process of a convolutional 2D neural network for detection of shortened winding turns of a three-phase permanent magnet synchronous motor. Input datasets for aforementioned procedures have been created by sensing vibration data on the real motor using accelerometers with a possibility of artificially induce short circuit in the motor winding. Only simple pre-processing of a time signal has been done – the time waveform was reshaped into 2D greyscale images with a size of 64 x 64 points and led directly into the neural network. No pretrained network has been used – internal parameters have been learned from scratch. Learning process as well as inference of the network have been performed on a standard personal computer with nVidia GeForce RTX 2080 Ti graphics card and implemented usign Python in Keras/TensorFlow environment. Datasets for different working states of the motor, such as speed, torque, error type and its severity have been used. Training procedure of the network has been done within lower tens of minutes and final validation accuracy was 100 % in the most cases, while classification accuracy during inference process has reached the value of more than 99 %. Obtained results confirmed a fact, that faults' detection of the mechatronic system based on sensing of mechanical quantities and their evaluation is very reliable even in the case of electrical-based faults.**

Keywords—neural network, artificial intelligence, CNN, classification, vibrodiagnostics, PMSM, interturn short-circuit, Keras, TensorFlow, Python

I. INTRODUCTION

Nowadays, permanent magnet synchronous motors (PMSM) are widely used type of drives in electrical vehicles (EV) and within all other traction applications in industry, automotive and aviation domain. Such motor type overcomes complications of an overall AC motors group, and despite its higher price it has superior torque parameters, reduced torque ripple, high efficiency, high power-to-weight ratio, and simple control strategy [1]. Massive usage of this type of motor leads to higher attention on the sufficient health assessment methods and predictive diagnostics of PMSMs. One of the biggest problems of this motor type are interturn short circuits. A motor winding is under high stress caused by increased vibrations, increased temperature, and high voltages applied to the wires. These aspects lead to degradation of the wires insulation and accelerates a short circuit fault [2]. Since there exist a lot of PMSM models taking both the mechanical and electrical faults into the considerations [3], diagnostics can help not only in prevention of a defect, but it can reliably detect an incoming damage and e.g., change a control strategy or stop the machine immediately in case of detected fault.

In recent years, many publications have dealt with research and development of diagnostic methods and approaches trying to solve this issue. Zyiu et al. [3] demonstrated an approach based on state observations and high frequency signal injection methods, where a combination of both methods can be beneficial for detection and diagnostic of a fault severity. But these methods are suitable only for a state when a diagnostic system knows presence of a fault and is ready to measure its parameters. Kyeong et al. [4] proposed very simple and satisfactory method based on monitoring of the second order harmonic in the *D-Q* coordinates. Both previously mentioned methods, as well as other methods mentioned in many other articles (wide survey of the methods can be found in e.g. [5]), use the electrical quantities for diagnostic purposes. Nowadays, vibration diagnostics becomes a significant part of the mechatronic system, and it is beneficial to use it also for the interturn short-circuit detection. Vishwanath et al. [6] presented measurement and evaluation of a frequency spectrum of vibration signal as a diagnostic tool for winding shorts detection. Sawitri et al. [7] presented a system using back propagation neural network for detection of the vibration signature of the interturn short-circuits. However, these methods assume a good knowledge of a system to determine the exact fault frequencies, or they need strong data pre-processing before the signal is led to the input of the neural network. Skowron et al. [8] showed a principle using the convolutional neural network (CNN) for processing raw time signals of electrical quantities like phase currents, phase-to-phase voltages, and axial flux. This system with the CNN reached a high classification ratio even with no pre-processing of the input electrical data.

An approach presented in this article also uses no data pre-processing and also no deep knowledge of a system is needed – only raw vibration data is directly processed by a simple convolutional neural network.

II. EXPERIMENTAL SETUP DESCRIPTION

A special construction of the PMSM has been used as a vibration dataset generator. It is a standard three phase motor with two independent subsystems. Additionally, this motor has a special construction of the windings. It has an option to artificially induce interturn short circuits with a selectable severity from an outside of the motor as well as create an interphase short circuit. A special connection box with clamps (where individual winding's parts are connected), relay and thyristor are used to shorten the windings. Two accelerometers for vibration sensing have been mounted on a front bearing of the motor in perpendicular directions. Since an electrical interference caused by a power electrical signal for the motor control is quite high, it is necessary to use electrically isolated vibration sensors. In case of utilization of non-isolated sensors, signal to noise ratio would be small and the level of real vibration signal would be below the noise level and thus not useful. A shaft of the motor has been coupled to a dynamometer using a flexible clutch to control motor speed, load torque, and generated power. The Fig. 1 shows a detailed view on a test scenario with the PMS motor, the accelerometers, and a part of the dynamometer.

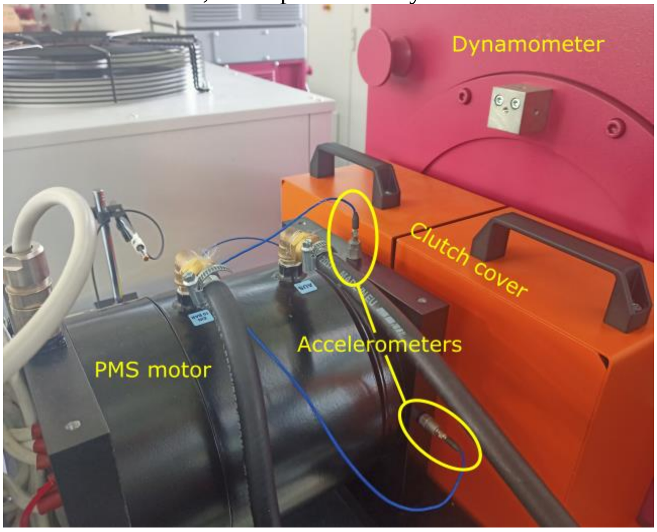


Fig. 1. Test scenario with the PMS motor, connected dynamometer, and the two acceleration sensors.

Both speed of the motor and moment of the dynamometer are controlled by a PC which is also generating UDP status packets on Ethernet interface. The packet is transferred each 100 µs (10 kHz) as a broadcast message and transmits all necessary information about a current operational status of the system and process values. These values inside the packet are represented mainly as 4-bytes single precision floating point numbers. The packet is acquired by NI CompactRIO (cRIO) controller module, where decoding, conversion of the numbers and basic calculation of additional quantities are done. Vibration measurement with the sampling rate of 51,2 kSps is also performed within cRIO using dedicated analog input card NI9234, providing supply for IEPE accelerometer and 24-bit signal acquisition. All values (received via the UDP packets as well as measured from the analog sensors) are automatically stored into one file, together with the error presence information, and labelled by current measurement time, type and severity of the error and loading torque of the dynamometer. A typical speed profile of the motor with the error information and corresponding vibration and acoustic signals can be seen in the Fig. 2. One complete testing cycle (speed profile) has a duration of ca. 2 minutes and includes the most of working speeds of the motor with max. speed of ca. 6500 RPM. A total of 72 test runs with different speed profiles, torque, type and severity of induced errors have been carried out and stored for later processing using neural network.

III. CONVOLUTIONAL NEURAL NETWORK

A. *Training dataset*

Since all data is stored in cRIO memory into one measurement file with the size of ca. 350 MB (complete batch of all test runs has a size of ca. 25 GB), only data acquired from the accelerometers is used for training the neural network.

Fig. 2. Top: analog data from microphone and accelerometers, bottom: speed profile (red line) and error presence (blue line) of the PMSM.

Accelerometer's signal (sampled at a rate of 51,2 kSps) represents a time waveform with the length of ca. 2 minutes. Raw floating point data is firstly normalized into `uint8` data type with a range of 0 to 255. The normalized data is re-sorted to a 2D greyscale image with the size of 64 x 64 samples, where shade of grey represents normalized value of the signal. With this size, the signal duration represented by one image is (64x64)/51200 = 80 ms. This period of time is a compromise between low limit frequency of the system (the longer the period the lower signal frequency that can be processed) and a resulting reaction time of the fault classification process (the longer the period the slower reaction time of the fault detection).

A set of labelled 2D images (fault/no fault) is created by a special application programmed in LabVIEW and exported as a binary file. This data file was later imported using Python into the Keras environment and used as a training or validation dataset in the process of designing of prospective structures of the neural networks. An example of the 2D images created from the time signal and representing three shortened winding turns in the first electrical subsystem and with zero load torque (the dynamometer drives the free-running motor), can be seen in the Fig. 3.

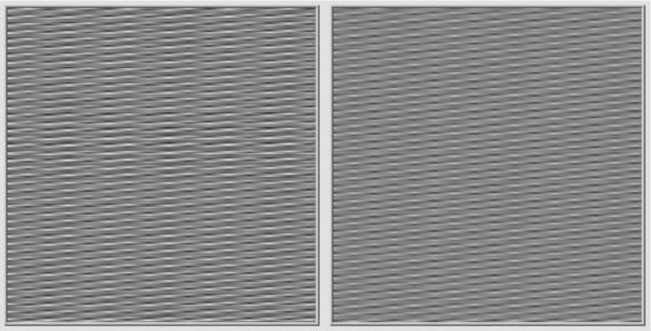


Fig. 3. Image representing faulty state (left) and healthy state (right) of the PMSM with the dimension of 64x64 values (pixels).

The image representing faulty state of the motor is on the left side while the image representing healthy state is on the right side. From the figure above it can be seen that the difference between healthy and faulty state is not clearly visible to the human eye, but the proposed convolutional neural network (as it will be shown later) is able to differentiate between these two states. Only for illustration, higher dimensions image can be seen in the Fig. 4, where the image on the left side has higher dimensions of 256x256 and the image on the right side is a fragment from the left side picture and has the dimensions of 64x64 values only. A thin red line in the image with higher dimensions represents the space, from which the small-dimensions image is created. The images have the same physical dimensions only for presentation purposes. Different dimensions of the input images were also used in the initial stage of the network design (256x256, 128x128, 32x32), but the final size of 64x64 data points has been evaluated as the best compromise between accuracy of detection and speed of the fault recognition.

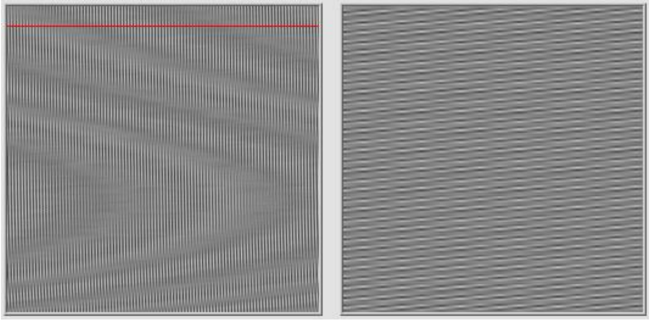


Fig. 4. Image with the size of 256x256 values on the left side and a fragment (64x64 values) on the right side representing the same waveform.

Examples of images containing acquired vibration data representing different faulty states of the motor (different torque, revolutions, speed, type of the fault, severity of the fault) can be seen in Fig. 5. A similar set of images is used as a real training set for the neural network.

B. *Network structure*

A final structure of the designed network is shown in the Fig. 7, while the textual description of the complete network structure in Keras application interface is shown in the Fig. 6.

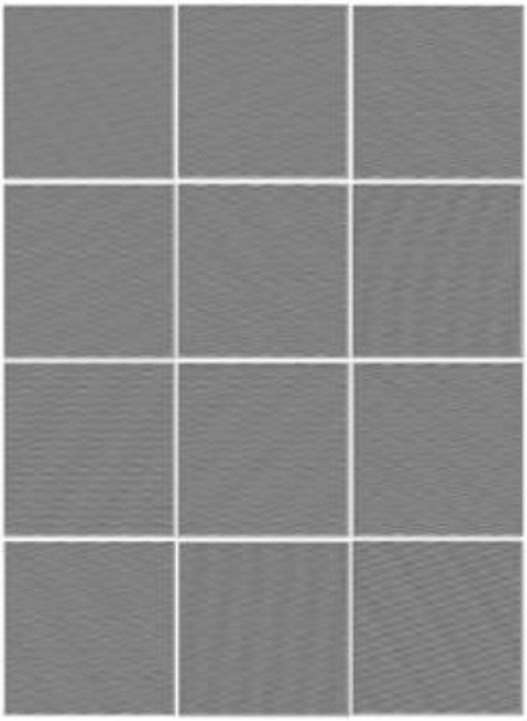
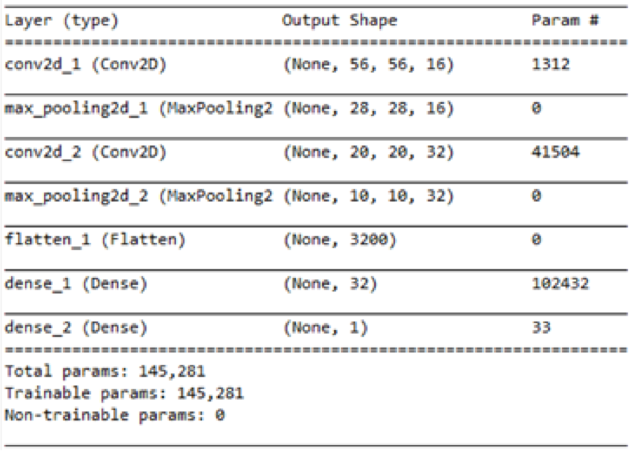


Fig. 5. Examples of different faulty states of the PMSM represented by 2D images.



```
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 56, 56, 16)        1312
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 28, 28, 16)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 20, 20, 32)        41504
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 10, 10, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 3200)              0
_________________________________________________________________
dense_1 (Dense)              (None, 32)                102432
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 33
=================================================================
Total params: 145,281
Trainable params: 145,281
Non-trainable params: 0
_________________________________________________________________
```

Fig. 6. Network structure exported from Keras.

The designed neural network contains two convolutional layers with a kernel size of 9x9 and two dense layers, with both ReLU and Sigmoid activation functions. Dimensions of the individual layers, the kernel size as well as the total number of parameters can be seen in the Fig. 6; the network has more than 145.000 trainable parameters (weights and biases) in total.

As an input, the 2D grey scale image with dimensions of 64x64 pixels is used. The network has only one neuron in the output layer, where zero value represents healthy state of the motor and a value of one represents detected induced fault of the motor. Other shapes of the neural networks have been also designed and tested, and their classification capabilities have been checked during development stage of the algorithm. Nevertheless, this structure, number of hidden layers, their dimensions, and size of kernels have been evaluated as the best compromise between the size of the network (which directly affects the inference time and with that also the reaction time of the fault classification) and final classification accuracy.

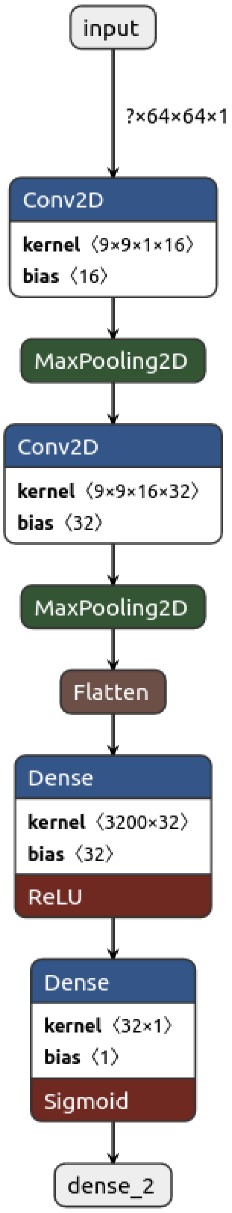


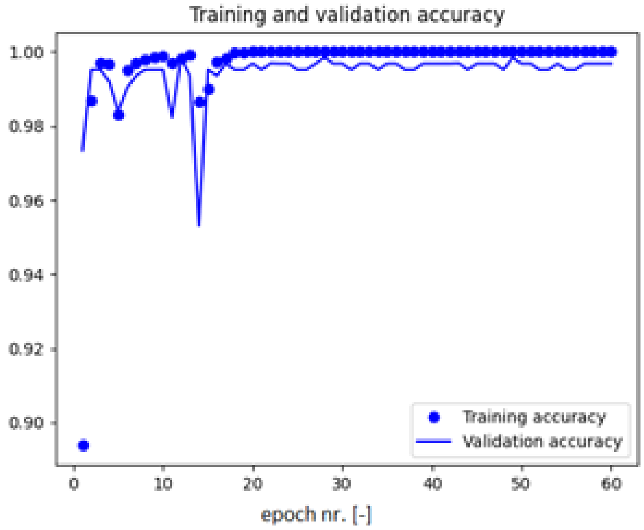
Fig. 7. 2D convolutional network structure.

C. *Training and clasiffication process*

The network has been trained with the dataset created from more test runs to cover complete input space – to train the network for the most working states of the PMSM system. In this case, only vibration data from the accelerometer in one direction has been used. A rule 10/90 has been applied during training and validation process (the input captured dataset was divided into two parts – 90 % of samples were used for training and remaining 10 % were used for validation). Resulting accuracy and loss curves, exported directly from Keras environment, can be seen in the Fig. 8 and the Fig. 9.

Fig. 8. Training and validation accuracy of the designed neural network.

Training as well as validation process of the network have been done on a standard desktop personal computer with Intel i7 quad core processor of the fourth generation with a speed of 4 GHz, 32 GB of the internal RAM and a dedicated graphics card nVidia GeForce RTX 2080 Ti, intended for gaming purposes, parallel computations and also very suitable for artificial intelligence algorithms development, training and inference. With this configuration of the development PC, proposed network structure and 60 input epochs, the training and validation process takes ca. 30 minutes.



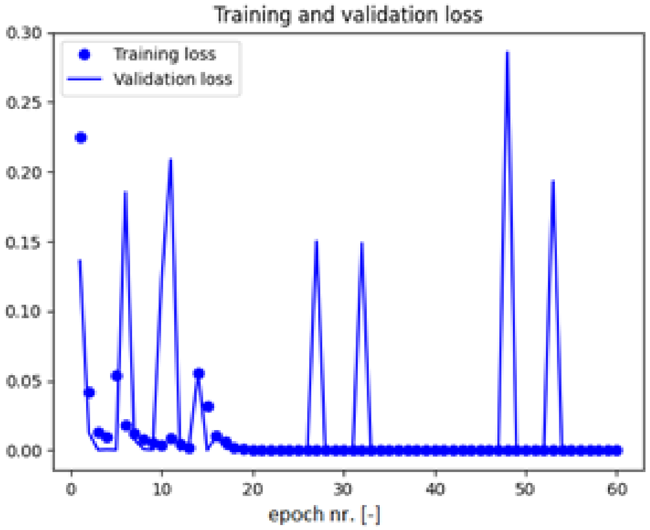


Fig. 9. Training and validation loss of the neural network.

Classification ability of the trained neural network is expressed in the Fig. 10.

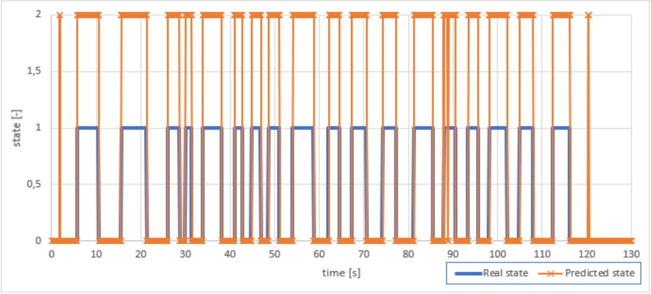


Fig. 10. Classification results of the trained neural network (bottom), speed profile of the test (speed profile).

Blue colour in the image represents the true class of the system (zero value means no error and value of one means faulty state), while orange curve states for the predicted class of the system obtained by inference process of the trained neural network model. The predicted value is multiplied by two only for better visualization. As it can be seen from the figure, the two curves are almost identical – total classification accuracy has been calculated as 99,1 %.

IV. DISCUSSION THE RESULTS

There are two major types of misclassifications hidden in the remaining 0,9 %. The first problem with the classification can be found at the end of the time period representing the error state (at the end of the transitions from the error state (value of one) to the healthy state (value of zero)), where the time delay caused by processing in the neural network of 80 ms occurs. This time corresponds to the duration of the vibration time signal represented in one image frame with the size of 64x64 data points.

The second classification problem is caused by the non-ideal image size. The current size of 64x64 contains 80 ms of the signal waveform. This value corresponds to the frequency of 12,5 Hz and the rotational speed of approx. 750 RPM. For this speed of rotation, less than one period of the fundamental harmonic of the input signal signal is represented in the image, and the network can hardly recognize the fault. Situation is getting even worse for lower speeds. The network could be more extensively trained for the state where low rotational speed is present by extending the training dataset with these states or the model of the network should be adapted for increased size of the image, however the second approach has unfortunately a negative influence on the reaction time of the fault detection system.

V. CONCLUSION

Detection of electrical based faults can be very reliable even when utilizing measurements of mechanical signals, such as vibrations generated by the faulty motor. The advantage of this approach compared to the electrical signals measurement is the speed of reaction and also the ability to detect only a small severities of the electrical fault. Detection based on the sensing of electrical quantities can be difficult in case of low rotational speeds and with small severity of faults. Nevertheless, there is no need to install additional sensors for electrical based detection of faults because electrical quantities are measured naturally for motor control purposes. However, installation of mechanical quantities sensors can be beneficial not only in case of fault detection, but also for predictive diagnostic of machines and their unwanted breakouts prevention. The 2D CNN proposed in this article provides satisfactory results for the fault detection of the PMSM (more than 99 %) from the vibration signal without any prior knowledge of the system or intensive signal pre-processing of the input data, like e.g., FFT analysis, which is definitely a tool for detection of motor faults as well.

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