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Short Circuit Fault Detection in Permanent Magnet Synchronous Motor Based-on Group Model of Data Handling Deep Neural Network

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***Abstract*—** Short circuit fault (SCF) in stator coils is one of the most common types of electrical faults. The expansion of this fault leads to the permanent demagnetization of the magnet, and causes irreparable damage to the machine in a short period. With the development of artificial intelligence technologies and various machine learning and deep learning techniques, an increase in fault detection accuracy has been achieved. In this paper, permanent magnet synchronous motor (PMSM) is investigated under normal mode and fault conditions, namely SCF in winding loops, phase to phase SCF and open circuit fault of one of the phases. Group Model of Data Handling deep neural network (GMDH-DNN) is used to produce a SCF detection model. Results of simulating the proposed method and the data extracted from the PMSM reveals that the accuracy rate of SCF detection in the winding loops of the PMSM in the proposed method is equal to 99.2%, which constitutes an improvement of 1.7% compared to other existing methods such as conditional generative adversarial network (CGAN). Moreover, simulating other existing methods - namely support vector machine (SVM), k nearest neighbors (KNN), C4.5, multi-layer perceptron (MLP), recursive deep neural network (RDNN) and long short-term memory networks (LSTM) – and comparing them with the proposed method, unveil that the accuracy of the proposed method for SCF detection in winding loops overweigh those of aforesaid existing methods.

***Keywords*—** Deep neural network; Short circuit fault detection; Permanent magnet synchronous motor.

1. INTRODUCTION

The existence of faults in information systems is one of the most important challenges in the world today. The occurrence of faults in complex systems can affect the behavior of the systems and cause irreparable losses. Electric machines are among the complex systems that are affected by SCFs. Also, the PMSM is one of the types of electric motors that are used in special and sensitive applications. Short circuit fault is one of the most common faults in PMSM and it may be thought that the occurrence of (SCF) in the inner rings is not important in the initial stages and with low intensity, but with the expansion of the fault and the increase in current caused by short circuit and field generation strong, leads to permanent demagnetization of the magnet and causes irreparable damage to the machine in a short period.

In this paper, a model based on a deep neural network under healthy and fault conditions on PMSM is presented. Therefore, the Group model of data handling deep neural network is used for SCF detection in PMSM. A GMDH-DNN is used to generate a SCF

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detection model. With the aim that the results of the proposed method will reduce the detection time, improve the accuracy, and improve the fault detection of the SCF in the PMSM.

Various faults occur in the PMSM motor. Some of the most important faults that have attracted the attention of many researchers are:

- SCF of stator coils
- SCF of two-phase coils together
- Connection opening fault

"SCF of the stator coils" due to factors such as scratches and cuts on the winding, high amplitude of peak voltages, conductive pollutants, overheating of the winding, aging of the insulation, and looseness and vibration of the wires. A "SCF of two-phase coils together" when two phases are connected [1]. The "connection open fault" occurs when the connections are separated from each other and a fault is created in the system. This article focuses on the three mentioned faults.

Fault detection methods can be classified into model-based methods, signal-based methods, artificial intelligence methods, and hardware-based methods. The use of these methods means that the detection of all types of faults can be effectively achieved. Many methods are applied to induction and reluctance motors, but not applied to PMSMs. In addition, PMSM fault detection has many research areas, the most important of which is that artificial intelligence-based methods are in the emerging field. Reinforcement learning, deep learning, and machine learning can be used in detection for higher accuracy. The subject of this research is deep learning. Deep learning is a branch of machine learning and a set of algorithms that try to model high-level abstract concepts using learning at different levels and layers. Deep learning is a new approach to the idea of neural networks that has existed for many years and shows itself in a new format every few years.

In [2], they investigated fault modeling methods for PMSMs and compared them. In this paper, a detailed study of different fault modeling methods of PMSMs and their comparison in terms of accuracy and computational time is presented. Fault modeling methods are classified into electric, magnetic, and numerical circuit methods. It was observed that for faults related to the stator of a PMSM, the method based on the electric circuit is preferable to other modeling methods. In the case of faults related to the rotor such as demagnetization, the method based on the magnetic equivalent circuit is generally followed for modeling the fault. Numerical methods are generally used to obtain accurate thermodynamic results.

In [3], a method for the SCF detection of the internal rings in the PMSM was proposed based on the residual current. After the effect of the first round, the fault was analyzed based on a simple mathematical machine model to evaluate the fault signatures, a finite element (FE) model was presented to obtain the healthy behavior of the machine, and the effectiveness of the proposed method was confirmed on a resistant PMSM with the help of permanent magnets.

In [4], the modeling and detection of PMSM winding SCF was presented using stator current characteristic analysis. This model provides the possibility of investigating the position and severity of the stator coil fault by using the electric circuit. The power spectral density was used to identify the SCFs of the stator coil. It was found that the third harmonic amplitude of the current is a distinguishing feature for detecting the SCF ratio. In [5], an efficient and accurate method based on a CGAN and an optimized sparse auto encoder (OSAE) was proposed to diagnose the intermediate inter-turn (ITSC) problem for PMSMs.

In this research, a combination of two types of signals is created to create a training set, which is enhanced by CGAN, and OSAE parameters are determined by the process of training networks. The Test results indicate that the proposed method for diagnosing this fault has a high accuracy of 98.9%.

In [6], a one-dimensional convolutional neural network was proposed to detect PMSMs. By analyzing the torque and current signals of the motors, it is possible to diagnose the motors under a wide range of speeds, variable loads, and eccentricity effects. By combining current and torque features, the classification accuracy of the proposed method reaches 98.85%, which is higher than classical machine learning methods such as k-nearest neighbor and support vector machine.

In [7], fault detection of PMSM short circuits was investigated based on deep reinforcement learning. A dueling algorithm deep q-learning neural network (DQN) was used for training and learning the developed sample dataset. The results show that the fault detection accuracy of the algorithm can reach 97.5%, while the speed of convergence has been improved and the time cost of fault detection has been saved.

In [8], a non-contact fault detection method using a magnetic leakage signal based on a wavelet scattering convolution network (WSCN) and a semi-supervised deep rule-based classifier (SSDRB) is proposed. Through the analysis of the magnetic equivalent circuit model, the magnetic leakage signal on the motor surface is selected as the fault signal. Defective motor prototypes are built for testing. By comparing with other methods, the superiority and efficiency of the proposed method are confirmed by using a small number of labeled data in different conditions.

In [9], a new approach based on electromechanical inverter was presented to detect stator SCF in PMSMs. It was found that the amplitudes of the second and fourth harmonic components of the torque signal are distinctive features that can be used to detect the ISCF of the stator winding in PMSM. With the proposed 2^{nd} and 4^{th} harmonic torque components, an inter-turn fault can be easily detected at an early stage.

In [10], a SCF detection method in PMSM for electric vehicles based on search coils (SC) was proposed. In this proposed method, the SCs are uniformly wound in the direction of the main flux of each phase, and the number of SCs is twice the number of phases, which leads to significant cost savings. Based on this structure, a new fault characteristic based on the negative sequence components of the sideband harmonics of the second carrier frequency in the SC voltage signal is proposed. As a result, this fault characteristic frequency component is not only clearer than the fundamental component used in the traditional SCs method.

By reviewing previous research that have been done in SCF detection in PMSM, it was observed that each of the methods, despite their many uses, still face challenges such as high error detection, low accuracy detection, complex model generation, high execution time, lack of generalizability and expandability. Therefore, in this paper, The GMDH-DNN is used to solve the most important challenge of previous research, SCF detection in PMSM. GMDH-DNN is utilized on this paper due to its ability to support a high number of layers, model generation with acceptable accuracy, low error rate, ability to support a large amount of data, etc. Next, in section 2, the proposed method and relevant details are explained. Finally, in section 3, the results are obtained, and in section 4, the conclusions are presented.

2. THE PROPOSED METHOD

In Fig. 1, the architecture of the proposed method for SCF detection in PMSM based on GMDH-DNN is shown.

2.1. GMDH Deep Neural Network

The GMDH or GMDH-DNN algorithm was first developed by Ivakhnenko [11] as a multi-variate analysis method for modeling and identifying complex systems. The main goal of GMDH is to establish an analytical function based on a feedforward network, each element of which forms a quadratic function whose coefficients are obtained using regression methods [12].

According to the GMDH algorithm, a model can be expressed as a set of neurons so that their different pairs in each layer are connected through a second-order polynomial equation and create new neurons in the next layers. The concrete and conventional definition of identifying a problem is to find the function $\hat{f}$ such that it can be approximated instead of the actual value of f in order to predict the output $\hat{y}$ for a given input vector $X = (x_1, x_2, x_3, \dots, x_n)$ in the closest possible state to the actual value of the output y is used. Therefore, M is a specific observation of a multi-input-single-output data pair such that Eq. (1):

$$y_i = f(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})(i = 1,2, \dots., M) \tag{1}$$

Now it is possible to train a neural network of GMDH type to predict the output values $\hat{y_i}$ for any specific input vector $X = (x_{i1}, x_{i2}, x_{i3}, \dots)$ that is:

$$\hat{y}_i = \hat{f}(x_{i1}, x_{i2}, x_{i3}, \dots, x_{in})(i = 1,2, \dots., M) \tag{2}$$

Now the problem is to determine a GMDH-DNN in such a way that the square of the differences between the actual output value and the corresponding predicted value is minimized, and thus:

$$\sum_{i=1}^{M} \left[\hat{f} x_{i1}, x_{i2}, x_{i3}, \dots, x_{in}) - y_i\right]^2 \to min \tag{3}$$

The general equations between inputs and output variables can be expressed using a discrete complex form of the Volterra series of functions in Eq. (4) [12]:

$$y = a_0 + \sum_1^n a_i x_i + \sum_1^n \sum_1^n a_{ij} x_i x_i + \sum_1^n \sum_1^n \sum_1^n a_{ijk} x_i x_j x_k + \cdots \tag{4}$$

This complete form of mathematical expression can be expressed as a system of several two-component sentences so that they contain only two variables (neurons) in Eq. (5):

$$\hat{y} = G(x_i, x_j) = a_0 + a_1 x_i + a_2 x_j + a_3 x_i x_j + a_4 x_i^2 + a_5 x_j^2 \tag{5}$$

where the coefficient a_i in Eq. (5) is calculated with the help of regression methods. So that the difference between the actual value (y) and the expected value ($\hat{y}$) is minimized for each pair of input variables X_i , X_j. In this regard, the coefficients of each relation of the order of two G_i are obtained for the optimal fitting of the output in the entire input-output data pairs. In other words:

$$E = \frac{\sum_{i=1}^{M} (y_i - G_i)^2}{M} \to min \tag{6}$$

In the main form of the GMDH algorithm, all possible states of two independent variables from the sum of n input variables are considered in order to form regression polynomials in the form of Eq. (5) so that the best fits of dependent observations (y_i, i= 1,2,…, M) in order to satisfy the least squares. As a result, $\binom{n}{2} = \frac{n(n-1)}{2}$ neurons in the first layer of the forward feed network from observations $\{(y_i, x_{ip}, x_{iq})(i = 1,2, \dots, M)\}$ are expanded for different values of $p, q \in \{i = 1,2, \dots, n\}$. In other words, in this case, it is possible to form M triple data $\{(y_i, x_{ip}, x_{iq})(i = 1,2, \ldots, M)\}$ from observations with the help of such form $p, q \in \{i = 1,2, \ldots, n\}$ exists:

$$\begin{bmatrix} x_{1p} & x_{1q} & \vdots & y_1 \\ x_{2p} & x_{2q} & \vdots & y_2 \\ \cdots & \cdots & \vdots & \cdots \\ x_{Mp} & x_{Mq} & \vdots & y_M \end{bmatrix} \tag{7}$$

With the help of a second-order subset in the form of Eq. (2) for each row of M triple data, the matrix equations are easily obtained as Eq. (8):

$$\mathbf{A} = \boldsymbol{Y} \tag{8}$$

where a is the vector of unknown coefficients of the second-order polynomials of Eqs. (9) to (12).

$$a = \{a_0, a_1, a_2, a_3, a_4, a_5\} \tag{9}$$

$$aY = \{y_1, y_2, y_3, \ldots, y_M\}^T \tag{10}$$

where a variable is the vector of output values of observations. It can be easily seen that:

$$A = \begin{bmatrix} 1 & x_{1p} & x_{1q} & x_{1p}x_{1q} & x_{1p}^2 & x_{1q}^2 \\ 1 & x_{2p} & x_{2q} & x_{2p}x_{2q} & x_{2p}^2 & x_{2q}^2 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 1 & x_{Mp} & x_{Mq} & x_{Mp}x_{Mq} & x_{Mp}^2 & x_{Mq}^2 \end{bmatrix} \tag{11}$$

The least squares method of multivariate regression analysis leads to the solution of coefficient equations in Eq. (12):

$$a = (A^T A)^{-1} A^T Y \tag{12}$$

Eq. (12) determines the vector of the best coefficients of Eq. (5) for the entire set M of triple data. It is worth noting that this method is repeated for each neuron of the next hidden layer according to the topology of the network [13-15]. Therefore, with this core, the model generation process is carried out for fault detection.

2.2. The Proposed System Model

As can be seen from Fig. 1, to implement the proposed method to reach the goal of the problem, which is to diagnose the short-circuit fault in the PMSM based on GMDH-DNN, first the data is the set of data extracted at different time points from the synchronous motor. The permanent magnet is included in the proposed method. Then this data is pre-processed and the unused data is removed. In the following, the data that was converted into a coherent form after applying pre-processing is converted into an acceptable form for simulation. At this stage, the data is usually converted into Excel and a consistent format.

The next step is data normalization, explained in detail in the next section. In the modeling process, the data of the problem are placed between the range [0, 1]. Normalization makes the produced models not complicated and increases the accuracy of SCF detection in PMSM based on GMDH-DNN.

The final data which is the output of the pre-processing phase algorithm should be divided into two parts, which are: Training and Testing data. Training data are proposed to teach GMDH-DNN methods. Training data usually make up 70% of the dataset. The Testing data that make up 30% of the total dataset are used to evaluate and validate the proposed method to SCF detection in PMSM based on GMDH-DNN.

After the Training and Testing data are separated, the Testing data are applied as input to the GMDH-DNN model. Then a model is produced based on the Testing data. The Test data are applied to this model and based on the available data, fault detection validation is done. Finally, the proposed method is evaluated and metrics such as accuracy, precision, recall, error, etc. are calculated.

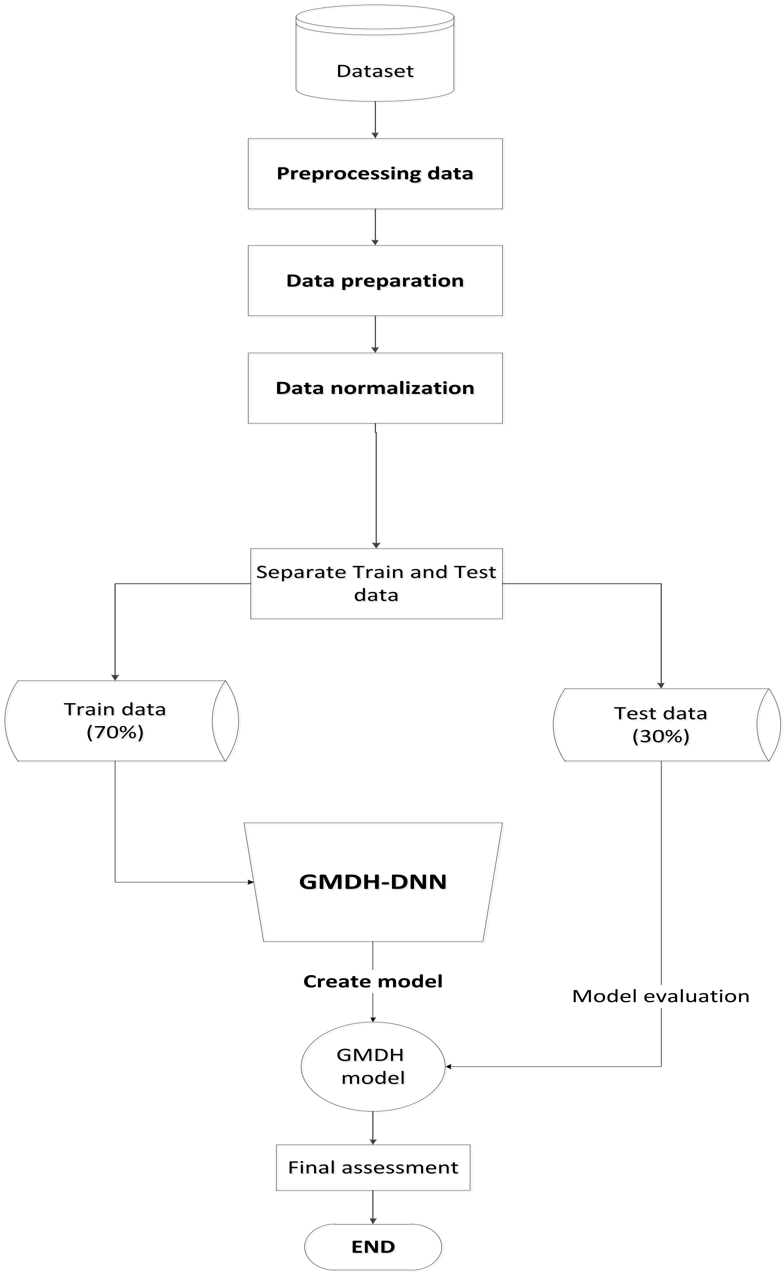

Fig. 1. Architecture of the proposed method for SCF detection in PMSM based-on GMDH-DNN.

2.3. Data extraction using PMSM

In this paper, one of the common types of electrical faults in electric motors, i.e. the SCF of the stator winding of the PMSM, has been evaluated. Therefore, first, the motor that is designed under fault conditions and can change the state from a healthy state to a fault state starts working, which is done in the simulation environment of MATLAB software. It is worth mentioning that in the simulation for the motor drive, after converting the three-phase current from the *abc* domain to the *dq* domain, these obtained currents are used for comparison at the input. Finally, by obtaining the voltage V_q and V_d and applying it to the PWM converter. The motor is started and controlled. In Fig. 2, the circuit model designed for the PMSM under the condition of SCF in the winding is shown.

First, the motor starts working in a healthy state, and the investigated faults are also generated in the motor in different intensities. At this time, the data required for the design of the intelligent fault detection system (FDS) [16] are extracted from the normal (healthy) state of the motor and the states to be evaluated. Then, 70% of the extracted data is used to train the GMDH-DNN algorithm and the other 30% of data is used to evaluate the designed system before it is used as a FDS on the motor.

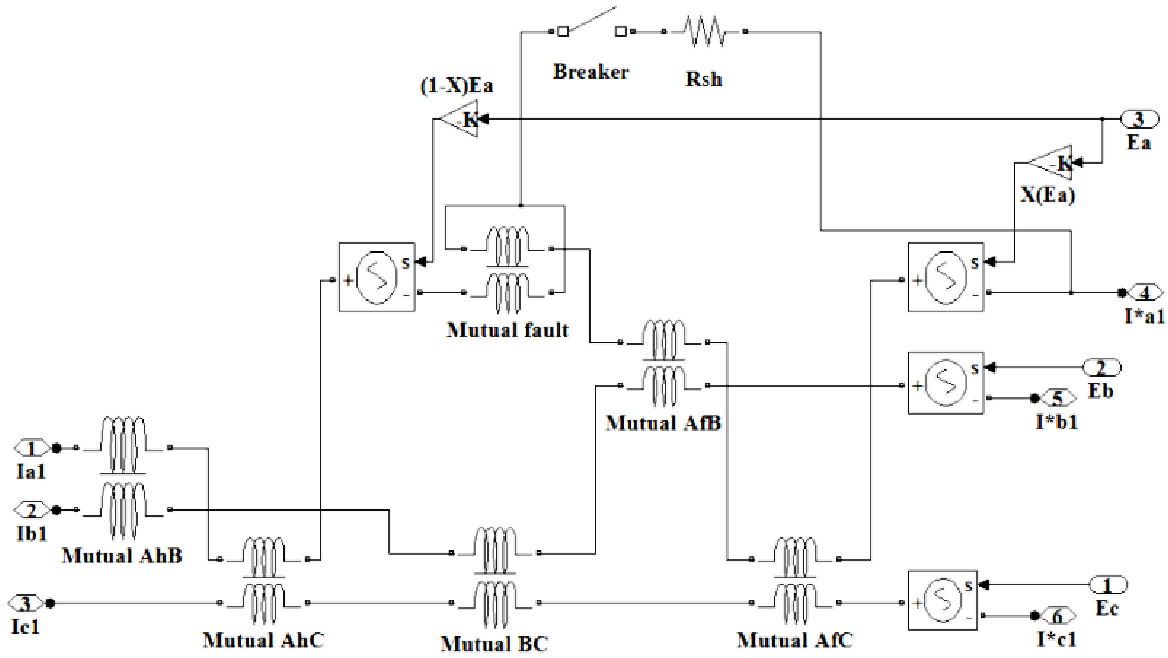

Fig. 2. Circuit model designed for PMSM under SCF condition of in the stator winding.

2.4. SCF detection in PMSM

In this section, simulation steps are explained to SCF detection in PMSM.

2.4.1. Dataset

In this paper, three-phase current value and rotor position information are collected at several consecutive sampling moments to be made into several sequences, which in turn are entered into the GMDH-DNN algorithm. After completing the input sequences, the final output value is obtained to pass through the fully connected neural network, and the output of the network is the predicted three-phase current value at the next sampling moment.

In order to obtain a robust GMDH-DNN model and remove the interference of motor acceleration, deceleration or torque waves, etc., current waveform and rotor position information in different operating modes (different speed or different load torque) are collected as Training data. The trained GMDH is then imported into Simulink for current prediction.

Then, 70% of the data received from the PMSM at different time points are used as Training data to generate the GMDH-DNN model. Moreover, 30% of the data are also used to test and evaluate the produced model for SCF detection in the PMSM.

2.4.2. Data pre-processing

Before the data is introduced into the proposed method, the desired data is pre-processed and the missing values are removed. Then, the data that was converted coherently after applying pre-processing is converted into an acceptable format for simulation tools.

Various methods have been proposed to apply pre-processing on the data, which include:

- Data Cleanup
- Data Aggregation
- Data Transitions
- Data Reduction

The proposed strategy is to analyze the data and identify if a row or column has useless values. Then examined the values before and after the sample that has an unused value and calculate their average. Finally, the unused value is replaced with the obtained average [17].

2.4.3. Data preparation

After the unused data are destroyed, the data must be prepared. For this purpose, the pre-processed data is converted into an acceptable format for simulation tools. After the dataset superficially is analyzed, the normalization process should be done on the data.

2.4.4. Data normalization

In the pre-processing stage, in order to obtain better results, the values of each feature of the used Robin dataset are normalized from 0 to 1. In other words, the dataset is mapped in the form of a matrix, and by changing the rows of the matrix, the normalization operation is done. Normalization is due to achieving higher accuracy. The Eq. (13) has been used to normalize the dataset [18].

$$\text{Normalize}(x) = \frac{(\mathrm{x}-\mathrm{X}_{\min})}{(\mathrm{X}_{\max}-\mathrm{X}_{\min})} \tag{13}$$

where X_{max} and X_{min} are the maximum and minimum values in the domain of the Xth feature. After normalizing the data, the values of all attributes are in the [0, 1] range.

2.4.5. Separation of training and testing data

Sampling the desired data is one of the steps of data mining that is considered in this paper. There are different sampling methods, the three most important of which are [19]: i) random sampling; ii) stratified sampling; and iii) balance sampling.

Random sampling is one of the simplest sampling methods that operates randomly and separates data from the main dataset as training and testing data to the desired extent.

The stratified sampling method is also one of the improved methods of the random method. This method performs the sampling process based on probability and still selects the data as a percentage. The balanced sampling method is one of the methods that select the required data in a balanced way from among the available categories and classes, which is used in this paper [19].

2.4.6. Application of GMDH-DNN algorithm

In the proposed method, after extracting the dataset, some data are considered healthy data (normal conditions) and some as problem data (including the opening of the stator winding connections (SWC), the short circuit of the two-phase windings, the intern turn short circuit of each phase) 70% of the data are used to generate the GMDH-DNN model. Fig. 3 shows how to build a model for SCF detection in a PMSM by GMDH-DNN. After the correct operation of the designed system in the training and testing phase, it is used as an intelligent FDS that has a sampling, analysis, and analysis system based on the GMDH-DNN trained along with the PMSM. Therefore, the test data, which is 30% of the total dataset, is entered into the GMDH-DNN model and the SCF in the PMSM is detected.

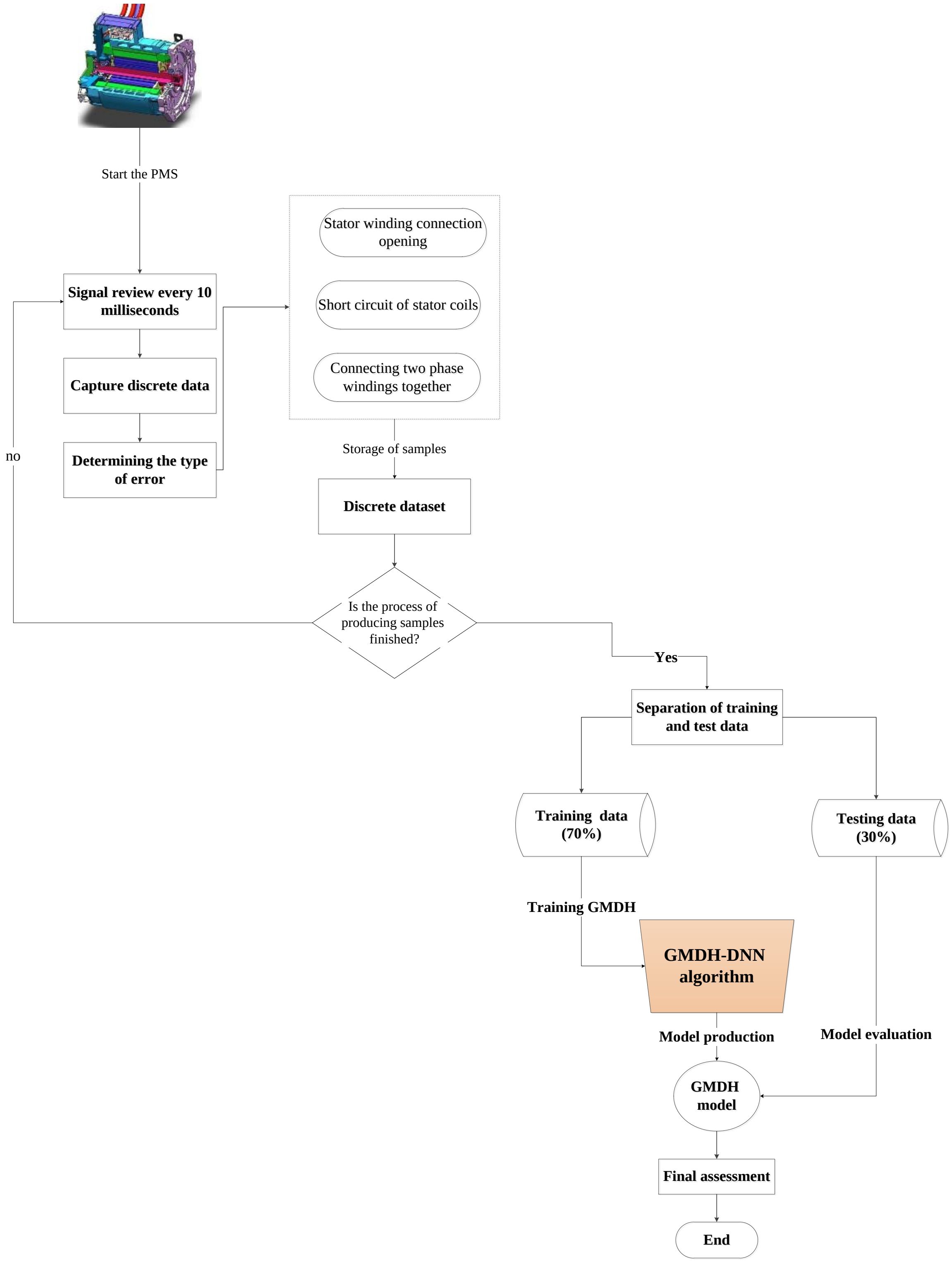

Fig. 3. SCF detection model in PMSM by GMDH-DNN.

3. EXPRIMENTAL RESULTS

In this paper, the MATLAB 2015a tool is used for simulation. Also, the dataset and data used by PMSM are produced. Therefore, PMSM starts producing data. The generated data are divided into two categories: training (70%) and testing (30%). The training data are implemented by MATLAB 2015a software to GMDH-DNN algorithm and a detection model is produced. Finally, the test data is entered into the model and results are obtained. In Table 1, the parameters of the proposed GMDH-DNN are shown.

3.1. Evaluation Metric

In order to evaluate the results of the proposed method, metrics such as accuracy, precision, recall, error, and F- Measure are presented to the Eqs. (14) to (18).

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

The True Positive (TP) parameter represents the number of data that are correctly detected. The False Positive (FP) parameter also indicates the number of data that were not correct, but the proposed method detected that sample as correct. Eq. (15) shows the recall metric.

$$ReCall = \frac{TP}{TP+FN} \tag{15}$$

The False Negative (FN) parameter indicates the number of data that are not correct and are also recognized as correct. Eq. (16) shows the accuracy metric.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{16}$$

The True Negative (TN) represents the number of data that have the correct class and are detected as incorrect. Eq. (17) shows the F-Measure metric.

$$F - Measure = 2 * \frac{precision * ReCall}{precision + ReCall} \tag{17}$$

The error rate metric of the proposed method is calculated based on Eq. (18).

$$Error = 1 - \frac{TP+TN}{TP+TN+FP+FN} \tag{18}$$

Table 1. GMDH deep neural network parameters

Parameter	Value
Learning rate	0.001 [MS]
Reduction of reward	0.9
Replace the target	200
Memory size	500 MB
batch size	26

3.2. Simulation Results of the Proposed Method

In this section, the obtained results are analyzed to detect the following three types of faults: i) SWC opening fault; ii) SCF of stator coils and iii) two-phase short circuit fault.

Therefore, the results of the proposed method will be examined and compared to detect the types of faults of the opening of the SWCs, the SCF of the stator winding rings, and the connection of the two-phase windings.

By applying the dataset to the proposed method, results such as precision, accuracy, recall, error, mean squared error (MSE), Root Mean Square Error (RMSE), and MAPE were obtained. Fig. 4 shows the results of GMDH-DNN training and testing on PMSM data to detect the opening fault of the SWCs.

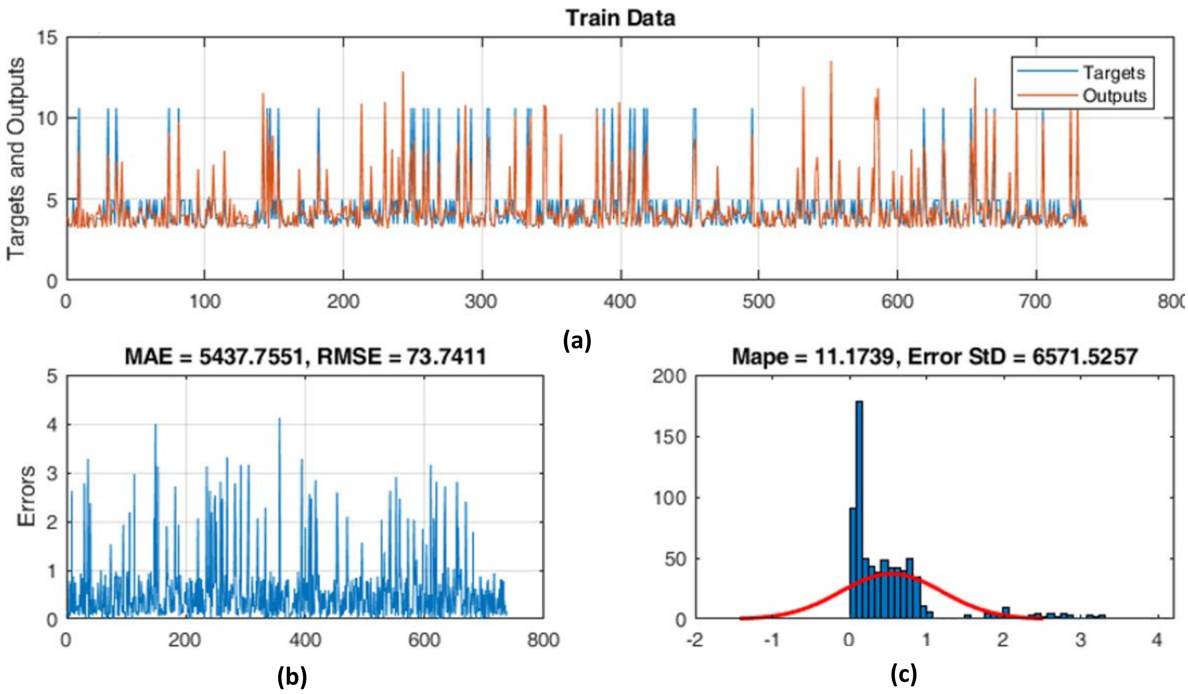

Fig. 4. The results of GMDH-DNN training on PMSM data to detect the stator winding rings of the SCF: a) random sample number training data and actual value; b) error among output and actual value; c) the standard deviation error value histogram.

As can be seen from Fig. 4 and Fig. 5, the training error rate for detecting the SCF stator winding rings is approximately equal to 0.8% for the test process and 0.9% for the training process.

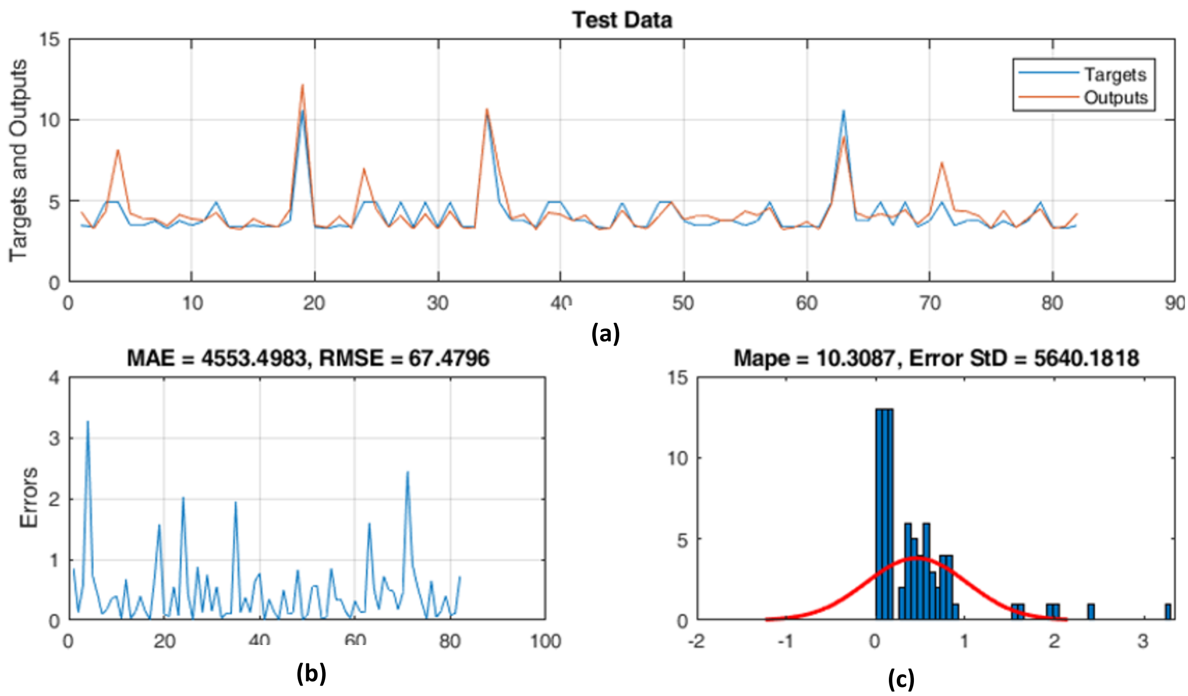

Fig. 5. The results of GMDH-DNN testing on PMSM data to detect the stator winding rings of the SCF: a) random sample number testing data and actual value; b) error among output and actual value; c) the standard deviation error value histogram.

On the other hand, the standard deviation of GMDH-DNN for PMSM data training is equal to 6571.5257 and for the GMDH-DNN model testing process is equal to 5640.1818. The results obtained from the training and testing process of the proposed method indicate the efficiency and optimal performance of the method used in this research. In Fig. 6, the results of accuracy, error, precision, and recall of the proposed method to detect the stator winding rings of SCF are shown.

As can be seen from Fig. 6, the accuracy rate of SCF detection using the proposed method to detect the SCF of stator winding rings is equal to 99.2%. The precision rate of the proposed method is 99.6%, the recall rate of the proposed method is 98.4%, and the error rate of the proposed method is 0.8%. In another experiment, in order to evaluate the performance of the proposed method compared to other methods, several other algorithms have implemented and compared the obtained results with the proposed method results.

In this section, the results of the proposed method are compared with other methods such as SVM [20], KNN [21], C4.5 [22], MLP [23], RDNN [24], and LSTM [25]. Thee methods are among the most important methods of artificial intelligence and data mining. The SVM algorithm works based on the feature vector. KNN algorithm based on similarity and neighbors, C4.5 algorithm based on decision tree and MLP, RDNN, and LSTM algorithms based on neural network and deep learning.

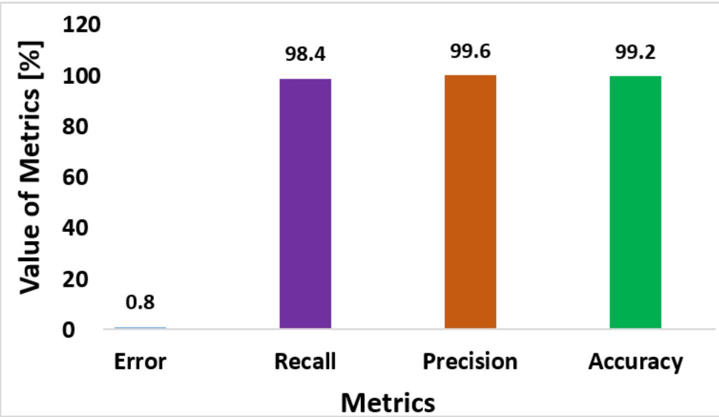

Fig. 6. The results of accuracy, precision, recall, and error of the proposed method for detect the SFC in stator winding rings.

Table 2 shows the comparison of precision, accuracy, recall, and error of the proposed method for the SCF of the stator coils with other methods.

Table 2. Precision, accuracy, recall, and error of SFC of the stator winding rings of the proposed method compared to other methods.

Method	Accuracy [%]	Precision [%]	Recall [%]	Error [%]
The Proposed method	99.2	99.6	98.4	0.8
LSTM	96	98.54	97.32	4
RDNN	95.12	97.8	97.09	4.88
MLP	92.34	94.76	97.1	7.66
C4.5	92.64	94.44	97.72	7.36
KNN	90.94	92.44	97.89	9.06
SVM	89.94	90.96	98.3	10.06

As shown in Table 2, the accuracy of the proposed method is equal to 99.2%, the average accuracy of other methods is also equal to 92.83%, which is the accuracy of detecting the SCF of the stator coils in the proposed method compared to other methods. It has improved by about 6.37%. The precision rate of the proposed method is 99.6%, and the average precision of other methods is 94.82%. The degree of improvement in the detection precision of the SCF of the stator coils in the proposed method is about 4.77% compared to other methods. The recall rate of the proposed method is 98.4%, and the average recall of other methods is 97.7%. The rate of improvement in detecting SCF of the stator coils in the proposed method compared to other methods is about 0.695%.

Table 3 shows the comparison of precision, accuracy, recall, and error of the proposed method to detect the opening fault of coil connections to other methods.

Table 3. Precision, accuracy, recall, and error of connection opening fault of the proposed method compared to other methods.

Method	Accuracy [%]	Precision [%]	Recall [%]	Error [%]
The Proposed method (GMDH-DNN)	98.31	98.98	95.6	1.68
LSTM-DNN	96.2	98.96	94.14	3.8
RDNN-DNN	95.7	98.43	94.11	4.3
MLP	93.28	95.79	94.12	6.72
C4.5	93.19	95.06	94.73	6.81
KNN	91.29	92.86	94.9	8.71
SVM	90.46	91.59	93.31	9.54

As shown in Table 3, the accuracy of the proposed method is equal to 98.31%, the average accuracy of other methods is also equal to 93.35%, and the accuracy of detecting the connection opening fault in the proposed method has improved by 4.96% compared to other methods. The precision rate of the proposed method is 98.98%, and the average precision of other methods is 95.49%. The recall rate of the proposed method is 95.6%, and the average recall of other methods is 94.21%. The recall rate of improvement in the detection of connection opening faults in the proposed method compared to other methods is about 1.38%.

Table 4 shows the comparison of precision, accuracy, recall, and error of the proposed method to detect the fault of connecting two-phase windings compared to other methods.

Table 4. Precision, accuracy, recall, and error of the proposed method to detect the fault of connecting two phase windings compared to other methods

Method	Accuracy [%]	Precision [%]	Recall [%]	Error [%]
The Proposed method	97.2	99.8	98.2	2.8
LSTM	95	98.06	97.32	5
RDNN	94.87	97.46	97.09	5.13
MLP	91.41	93.68	97.1	8.59
C4.5	91.03	92.65	97.72	8.97
KNN	92.69	94.32	97.89	7.31
SVM	88.44	89.13	98.3	11.56

As shown in Table 4, the accuracy of the proposed method is equal to 97.2%, and the average accuracy of other methods is also equal to 92.24%, which is the accuracy of detecting the fault of connecting two phase windings together in the proposed method compared to other methods. The methods have improved by about 4.96%. The Precision rate of the proposed method is 99.8%, and the average Precision of other methods is 94.21%. The improvement in the Precision of detecting the fault of connecting two-phase windings in the proposed method is about 5.58% compared to other methods. The recall rate of the proposed method is 98.2%, and the average recall of other methods is 97.57%. The rate of improvement in the fault detection of two-phase windings in the proposed method compared to other methods is about 0.63%.

In this research, the results obtained from the implementation of the proposed method based on the algorithm according to the parameters mentioned in Table 1 of GMDH-DNN have been compared with those of the method reported in [7]. They show that the accuracy rate of the proposed method is 99.2% while it is 97.5% for the method reported in [7], which represents 1.7% improvement in the accuracy.

4. CONCLUSIONS

In simulating the motor under fault conditions, mfile, Simpower system and Simulink environments are used simultaneously and together. The PMSM is designed under fault conditions in the Simpower system environment, which is more accurate than the Simulink environment due to the use of circuit elements. Capabilities such as changing mutual inductance between phases and even creating mutual inductance within one phase due to the occurrence of faults have been taken into account. This has led to an increase in simulation accuracy. After examining several signals (patterns) that can be extracted from the motor under fault conditions, the values of the effective priority values of the three-phase stator currents have been selected as the best pattern for identifying the short-circuit fault and determining the defective phase, because - compared to other signals - it has the ability to identify the fault and the defective phase at the same time. By evaluating and testing the proposed method based on GMDH-DNN, it was observed that the training process of GMDH-DNN was carried out with acceptable accuracy and minimal error and created a simple and strong model. By analyzing the results on the types of SWC opening faults, stator winding rings SCF and connecting two phase windings together, it was observed that the accuracy, precision, recall, and error of the proposed method - compared to other methods including LSTM, RDNN, MLP, C4.5, KNN, and SVM - have improved significantly.

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