International Journal of Power Electronics and Drive Systems (IJPEDS)
Vol. 14, No. 1, March 2023, pp. 185~198
ISSN: 2088-8694, DOI: 10.11591/ijpeds.v14.i1.pp185-198

Neural network based detecting induction motor defects supplied by unbalanced grid

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Article Info

Article history:

Received Oct 28, 2022
Revised Dec 1, 2022
Accepted Dec 6, 2022

Keywords:

1D CNN
ResNet architecture
SCIM faults identification
Stator electrical faults
Unbalanced grid

ABSTRACT

Predictive diagnosis of motor defects can reduce repair and downtime costs of electrical equipment. This paper presents the results of a research on the effectiveness of the defect classification and recognition system based on convolutional neural network to detect defects in a squirrel-cage induction motor based on the stator supply voltage and output phase currents when supplied from an industrial grid of limited power with possible voltage asymmetry and harmonic distortion taken into account. In this work a simulation model, implemented in MATLAB/Simulink, is proposed to investigate unbalanced conditions. The mathematical model has been verified on a physical test bench and then used to create a database of currents from measured asymmetric grid voltages in the presence of defects such as short circuit between turns of one phase, rotor bar breakage, rotor eccentricity and bearing defects. The classification quality of all defects in the neural network was 72%, with the exclusion of intercoil short circuit defect and the merging of different bearing defects, the quality of the model was achieved 91%. A further increase in the quality of the defect recognition system is due to a building up modification of the neural network architecture.

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1. INTRODUCTION

Squirrel-cage induction motors (SCIM) are widely used in all areas of human activity and currently consume more than half of the world's electrical power. Hence, both the performance of technical operations and the energy efficiency of the electricity consumption depends on the actual condition of the SCIM. To ensure long service life of high performance SCIM, it is necessary to perform early diagnosis of failures, defects or malfunctions in operation. This paper focuses on the investigation of slowly developing defects, the occurrence and development of which can be registered and predicted before an emergency situation. These defects include various types of short circuits (inter-turn short circuit, inter-phase stator short circuits, etc., caused, for example, by insulation degradation or increased vibrations), rotor bar failure, small eccentricity values, various bearing defects (inner/outer raceway defects, and rolling element defects).

Nowadays, different methods based on the physical principles are being developed for diagnosing SCIM defects based on measuring the following quantities [1]: vibration, emitted acoustic noise, temperature, partial discharges, electric current, electromagnetic field characteristics, electric power, and others. There are a number of works aimed to carry out a comparative analysis of the effectiveness of these methods for various defects [2]–[5]. In this paper the development of current analysis method is proposed allowing to investigate SCIMs working in long steady-state conditions, typical for many technological processes without their stopping both at supplying from autonomous voltage inverter [6] and at supplying from grid [7]. Various methods of signal processing are used to analyze current and voltage peaks: frequency (fast Fourier transform), time (time series analysis, Park transform), frequency-time (wavelet transform), and intelligence (neural networks, fuzzy logic and genetic algorithms).

A number of researchers are trying to apply different neural network architectures to detect faults. One of the most frequent faults are electrical defects in stator windings, which account for up to 40% of all cases [8]. A hybrid neural network (combination of self-organizing Kohonen (SOM) and multi-layer perceptron (MLP) networks) has been used to detect one or two faults but with no load [8], lightweight 1-D convolutional neural network (CNN) architecture along with maximal overlap discrete wavelet transform [9], [10] to detect electrical and/or mechanical defects in the rotor, the artificial neural network (ANN) aided by the Clarke transform when open-circuit fault detection in the IGBT inverter happens [11], neural network and hidden Markov model together (NN-HMM) to detect rotor eccentricity faults using current measurements [12], ANFIS-based neuro-fuzzy network also to detect mechanical defect in machine rotor [13], [14] application C4. 5 DT and MLP ANN has made it possible to determine short circuits under unbalanced grid and variable load [15], self-organizing maps neural networks based on active and reactive power components [16]. The active use of neural networks comes from their efficiency of 90% [9], [17], and in some cases up to 100% [18].

This paper proposes a solution to the problem of classifying SCIMs defects based on the intelligent approach of analyzing the frequency and time dependencies of currents and voltages obtained from a mathematical model under the conditions of unbalancing and harmonic distortion supply voltage. The aim of the study is to confirm the hypothesis that it is possible to detect and classify defects by intelligent means from electrical measurements under operating conditions. To test the hypothesis, datasets obtained by mathematical modelling in MATLAB package are used. It allows collecting large datasets for training the neural networks. For variability of the data corresponding to the same defect, the supply voltages measured on the physical test bench of the three-phase grid at different time intervals. The depth (development stage) of the defect in the mathematical model also changed.

For this purpose, the dynamic model of SCIM is considered in section 2, which allows to take into account the presence of asymmetry of electromagnetic system of electric machine, caused by both external voltage and defects of electric machine itself. Section 3 briefly describes the methodology for introducing defects into the mathematical model of SCIM. Section 4 gives a methodology for obtaining a dataset in the presence/absence of defects. To do this, the mathematical model was first verified by tests on the bench. Then, to generate data for training and multiple simulations, long term measurements of the network voltages were taken and later used for mathematical modelling. Section 5 describes the structure of the neural network under study for solving the problem of defect identification and classification, as well as the network training algorithms. Section 6 sums up the main results of the research.

2. BASIC EQUATIONS OF INDUCTION MOTOR PROCESSES

There are significantly different approaches to SCIM modelling. The most accurate method of process research is the application of finite element analysis and specialized software packages. A considerable disadvantage of this method consists in significant computational time consumption. For example, in [19], [20] there are researches according to which when solving the same problem, the method of interrelated electrical subsystems (with application of winding functions method) reduces calculation time from hours to minutes. At the same time, the modeling accuracy of the coupled electrical subsystems method is substantially determined by the amount of input data of the SCIM and the veracity of the model. Since a large amount of experimental data is required to train and validate the neural network, this approach is used.

The mathematical description uses the assumption that a short-circuited rotor consisting of a number of phases equal to the number of rotor bars with winding coefficients equal to 0.5 can be represented by an equivalent three-phase symmetrical rotor winding reduced to the stator parameters. The defects of the rotor bars can be accounted by the symmetry breaking of the equivalent three phase winding. On the basis of mathematical models [21]–[23] here is dynamic mathematical model of the SCIM in vector-matrix form.

$$\dot{I} = L^{-1}\left(U - RI - \frac{\partial L}{\partial \gamma} \cdot \omega \cdot I\right) \quad (1)$$

Where $R = [R_s \; R_r]$ is the matrix containing the stator and rotor phase resistances; $L = \begin{bmatrix} L_{ss} & L_{sr} \\ L_{rs} & L_{rr} \end{bmatrix}$ is the matrix of mutual inductances between different stator and rotor phases respectively;

$I = [i_{ABC}\ i_{abc}\ ]^T$ is the matrix vector of instantaneous stator and rotor phase currents; $U = [U_{abc}\ 0\ ]^T$ is the matrix vectors of instantaneous stator phase supply voltages; γ is the rotor angle; ω is the angular speed. The description of SCIM (1) should be extended with the equations of rotational motion and electromechanical energy conversion given in [23]:

$$\begin{aligned} M &= \frac{1}{2 \cdot Z_p} \cdot I^T \cdot \frac{\partial L}{\partial \gamma} \cdot I; \\ M - M_l &= J \cdot \frac{\partial^2 \gamma}{\partial t^2}, \end{aligned} \tag{2}$$

where Z_p is the number of polarity pairs, J is the inertia moment, M and M_l are electromagnetic and resistant torques, respectively.

3. DESCRIPTION OF THE DEFECTS TO BE IMPLEMENTED

When building an intelligent defect detection and classification system, the following defects were initially considered: inter-turn short circuits in one phase of stator winding; symmetry violation of rotor electromagnetic system, which is equivalent to destruction or deterioration of conductivity of a certain part of rotor bars; mixed eccentricity of rotor; three types of rolling bearing defects (inner and outer raceway defect, rolling body defects). Well-known approaches were used to introduce defects into the mathematical model. For instance, the approach [23]–[25] was considered when introducing the defect caused by the presence of developing inter-turn short circuits associated with a decrease in insulation resistance and the appearance of additional current circuits. The approach increases the dimensionality of matrices in (1) by the number of short circuits. The principle of model complication is shown in Figure 1. The method allows taking into account the depth of the defect, the degree of insulation deterioration between the windings.

The rotor defect is introduced in a similar way [23]. This assumes that short-circuited rotor faults do not result in new circuits. When both stator and rotor defects are found, some relative coefficient, denoting the depth of the defect, is introduced. Proportional to this coefficient, the resistance of the phase in which the defect occurs and the mutual inductances of this phase with all other phases of both the stator and the rotor changes. In addition, the main inductance of the phase in which the defect occurs changes in proportion to the second degree.

Defects associated with the presence of rotor and bearing eccentricity are introduced in the same way: by taking into account the periodic variation of the air gap. Since all inductances in (1) are inversely proportional to the air gap and Carter coefficient, their influence can be determined according to [26]–[29]. A visualization of the defect introduction algorithm is given in Figure 1.

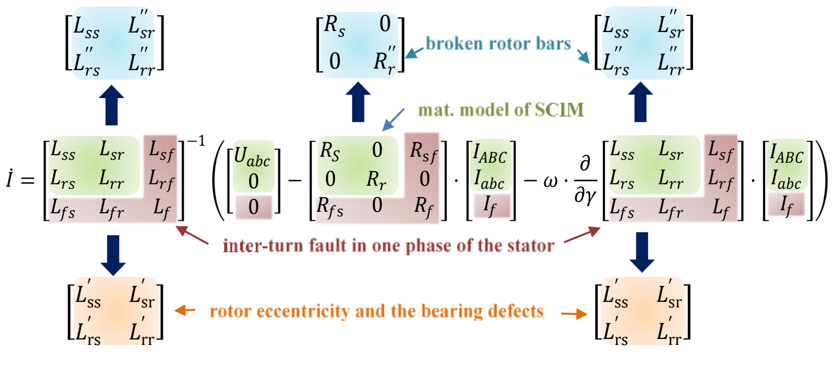
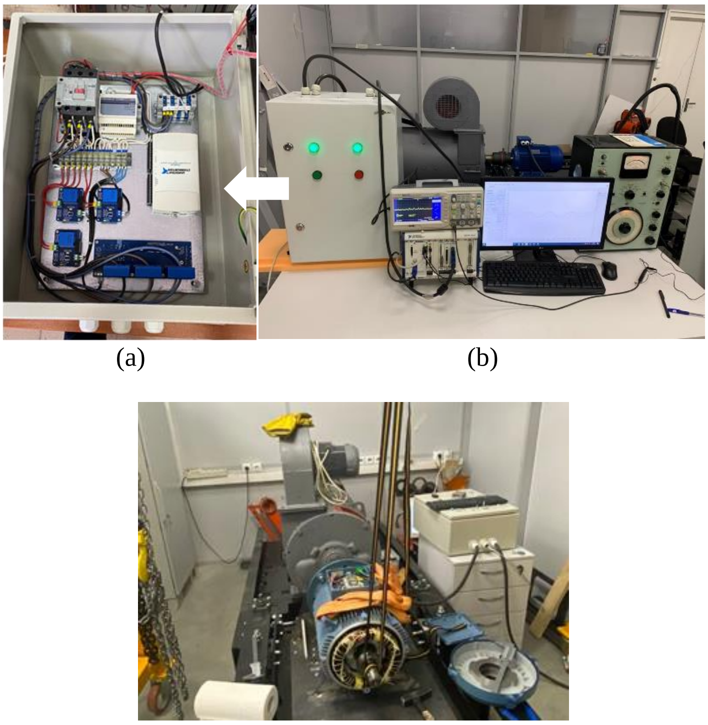


Figure 1. Changing the mathematical description of the motor depending on the implemented defects

4. DESCRIPTION OF THE EXPERIMENT

The objective of this work is to build a neural network for detecting and classifying defects in SCIM when it is supplied from unbalanced grid with nonsymmetrical voltages. The following approach was used to form the dataset to train the intelligent system. First, the computer model was verified in normal operation on the physical test bench shown in Figure 2. Figure 2(a) shows where the measurement block. Figure 2(b) shows data processing center and Figure 2(c) shows SCIM. Then continuous measurements of the three-phase network voltages with limited power were performed on the test bench. Multiple data sets at different time intervals and for different defects were obtained using these voltage measurements on the computer model.

The computer model used in the study is shown in the Figure 3. Within the functions in Figure 3, the (1) and (2) are presented with the possibility of introducing a defect.



(a) (b)

(c)

Figure 2. Data verification test bench (a) measurement block, (b) data processing center, and (c) SCIM

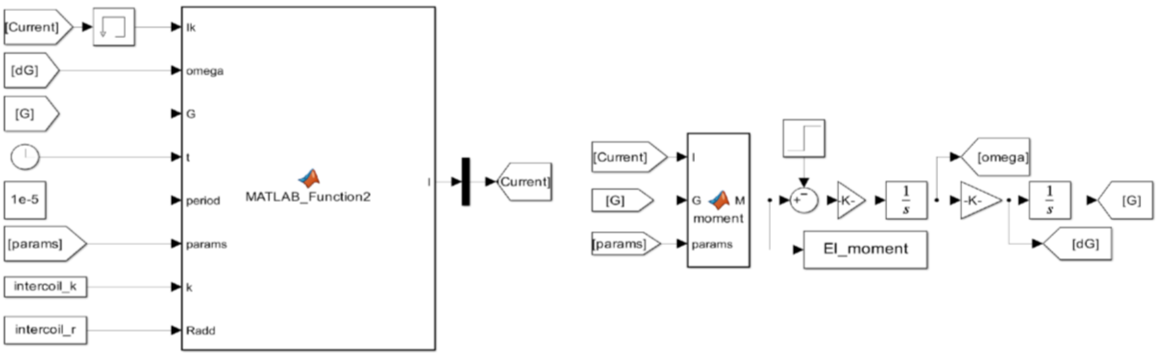
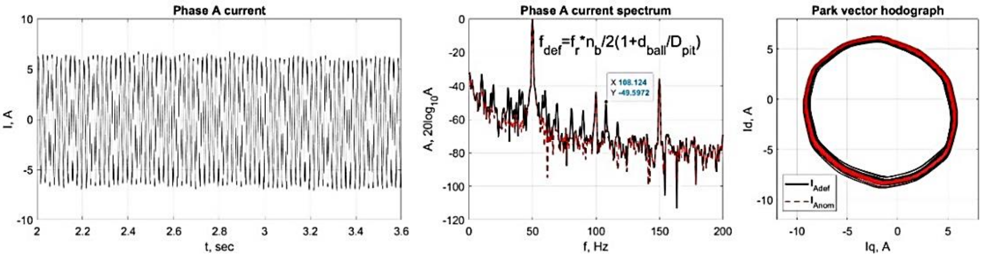


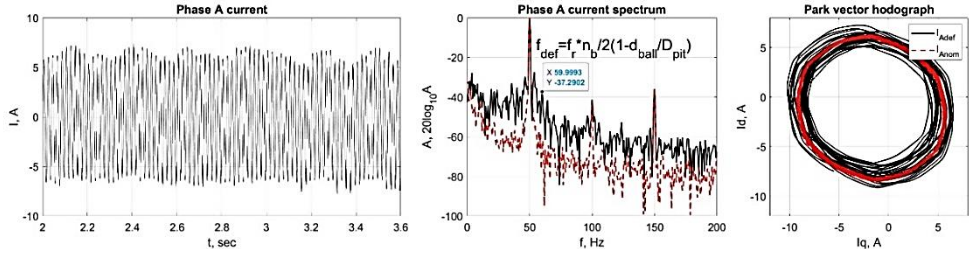
Figure 3. SCIM model with the possibility of applying defects

Figure 4 shows examples of the time dependences of stator phase currents of the SCIM at different defects, as well as a spectrum decomposition using the fast Fourier transform with a prior Kaiser window overlay [30] of one of the stator currents and the Park current vector travel time curve [31], [32]: (a) bearing inner raceway surface defect, (b) bearing outer raceway surface defect, (c) bearing body defect, (d) stator inter-turn short circuits, (e) rotor bar breakage, (f) static eccentricity.

It is worth noting that the results of the mathematical modelling shown in Figure 4 are in line with theoretical expectations in terms of the frequencies at which the expressed current harmonics appear. Frequencies f_{def} are corresponding to ISO 20958 "Condition monitoring and diagnostics of machine systems. Electrical signature analysis of three-phase induction motors". The following notations are shown in Figure 4, f_r is the rotor frequency in Hz; D_{pit} is the separator diameter, m; d_{ball} is the rolling ball diameter, m; n_b is the number of rolling balls; f_1 is the mains supply frequency in Hz; k, m are integers, s is sliding; p is the number of poles pairs.



(a)



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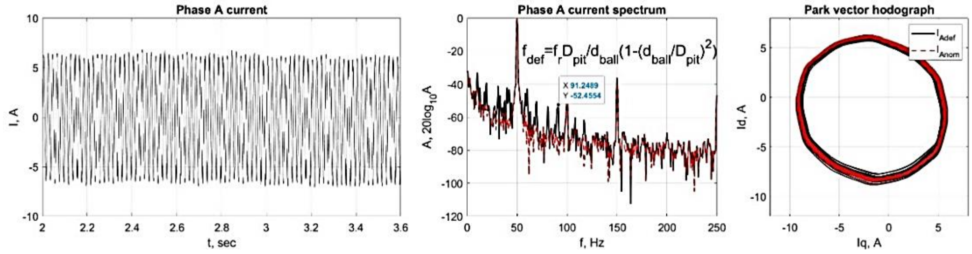
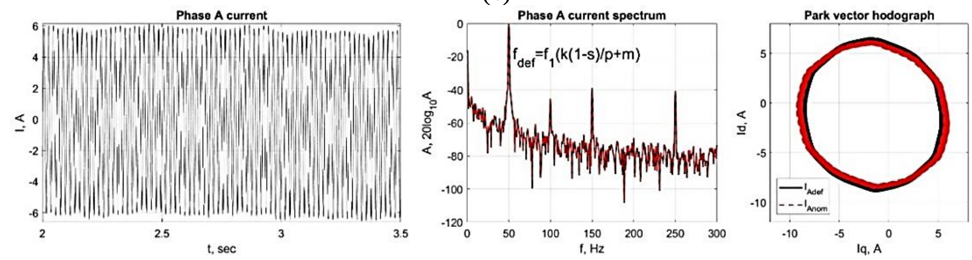
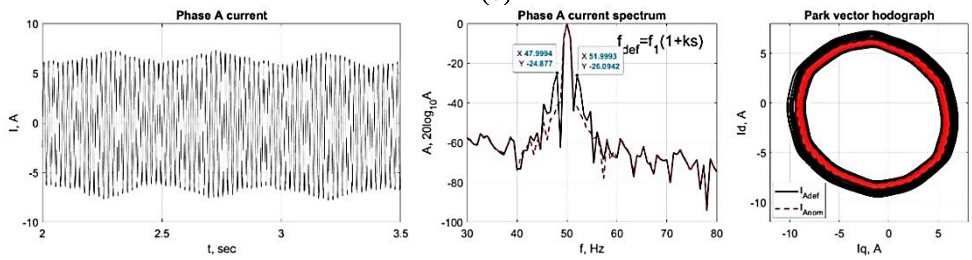


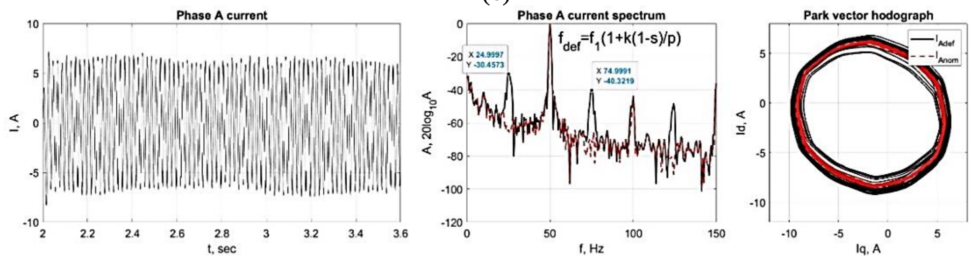
(c)



(d)



(e)



(f)

Figure 4. Single-phase curves and spectra, Park's hodograph and comparison with ideal operating conditions for bearing inner (a) and outer (b) raceway surface defect, (c) bearing body defect, (d) stator inter-turn short circuits, (e) rotor bar breakage, and (f) static eccentricity

5. DESCRIPTION OF THE NEURAL NETWORK TO BE TRAINED

The motor defect detection problem was reduced to a multi-class classification problem. A 34-layer convolutional neural network [33] based on the Standford ResNet architecture was used in this work, with cross entropy loss as the loss function. The input to the network is the data from the computer model of the SCIM, and the output of the network is one of the defect classes (including one class represented by the absence of any defects in the motor). The choice of network architecture was justified by the following factors. i) In Rajpurkar *et al*. [33], the authors of the network architecture achieved high network performance in classifying ECG (time series) signals; and ii) SCIM's data have similar shape and discreteness to ECG signals. A simplified diagram of the network architecture is shown in Figure 5.

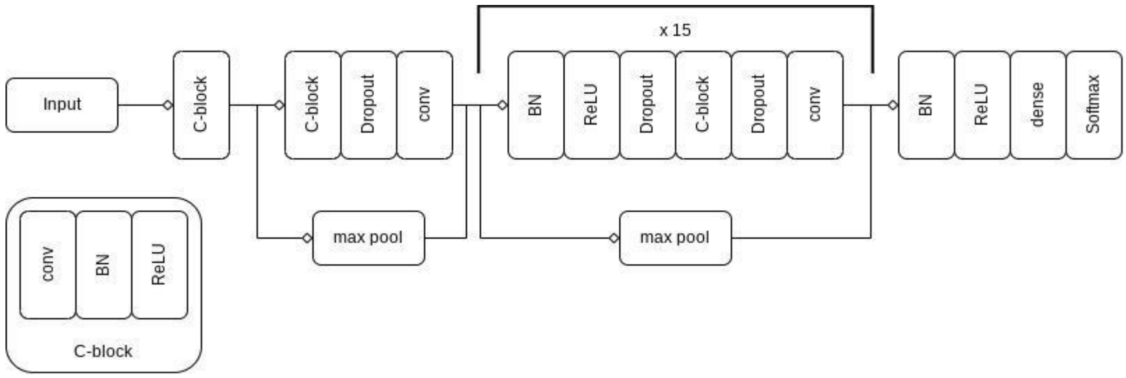


Figure 5. Simplified diagram of the neural network architecture

Two sets of classes were used in the training of the intelligent system: a full set (7 classes) and a modified set (5 classes). The completed set is represented by the following classes: bearing body defect, bearing inner rolling surface defect, bearing outer rolling surface defect, inter-turn short circuits within one phase, serviceable motor, rotor bar breakage and static eccentricity. The modified dataset does not include the class "inter-turn short circuits" but the classes "bearing inner raceway defect" and "bearing outer raceway defect" have been merged into one "bearing raceway defect". For the experiments, the following inputs were considered: raw measurement results, normalized time dependences and the Park vector travel time curves of the phase voltages and currents. The instants of the phase voltages ranged from -335 to 335 V and the phase currents ranged from -8 to 8 A.

During data analysis it was noticed that the form of currents travel time curves at static eccentricity significantly differs from other classes, while travel time curves of classes "bearing internal rolling surface defect", "bearing external rolling surface defect" and "stator inter-turn short circuits" largely repeat the form of travel time curves of data without introduced defect with a significant thickening of the travel time curve border caused by the appearance of higher harmonics of the spectrum. In this case, the form of the voltage time curves does not depend on the type of defect, but is determined by the current load of the power source, and therefore has approximately the same form for all classes. Examples of current time curves for all classes of defects are shown in Figure 4. A total of 5418 data files were used in the work, where each file corresponds to a signal of a certain defect class with a duration of 20 s. The distribution of classes in the data is balanced, each class is represented as 774 files. This data set was divided into 3 samples with stratification by defect class i) training sample (80%): 4334 files; ii) validation sample (10%): 542 files; and iii) test sample (10%): 542 files.

Due to computational limitations, it was not possible to use all 20s of data, as the signal frequency is 40 kHz, resulting in 800,000 points. Therefore, experiments with different signal durations from 0.5s to 3s were performed. The network was trained for 150 epochs on an NVIDIA GeForce 2080ti video card. The total amount of data was approximately 267 GB. The data was loaded into the TimescaleDB database, which gave quick access to the signal parts and allowed searching for the required files. However, due to the nature of the operating system (caching of data with frequent accesses) the use of more data is associated with even more computational and hardware loads, which may require the creation of a cluster of computing power and distributed computing between them, as well as the use of BigData solutions. Table 1 shows the metrics obtained on the test sample from the various experiments with the full set of defects.

Table 1. Summary of the result table (complete set of defects of 7 classes)

Inputs	Duration (s)	Number of test intervals	Accuracy	F1 macro	Precision macro	Recall macro
Raw data	0.5	2168	0.28	0.24	0.35	0.28
Normalized data			0.53	0.52	0.61	0.53
DQ			0.48	0.46	0.54	0.49
Raw data	1	1084	0.52	0.47	0.54	0.52
Normalized data			0.46	0.43	0.47	0.46
DQ			0.36	0.32	0.39	0.36
Raw data	2	542	0.72	0.71	0.76	0.72
Normalized data			0.64	0.62	0.66	0.64
DQ			0.69	0.66	0.7	0.69

6. RESULTS AND DISCUSSION

The best result was obtained by inputting raw measurements of voltages and currents with a duration of 2s. Figure 6 shows the error matrix obtained on the test sample in this experiment. Figure 7 shows the graphs of f1-score variation in the training and validation samples; (a) F1-macro, (b) F1-micro, (c) F1-score bearing body defect, (d) F1-score bearing inner rolling surface defect, (e) F1-score bearing outer rolling surface defect, (f) F1-score inter-turn short circuits within one phase, (g) F1-score faulty motor, (h) F1-score rotor bar failure, (i) F1-score static eccentricity, (j) F1 weighted.

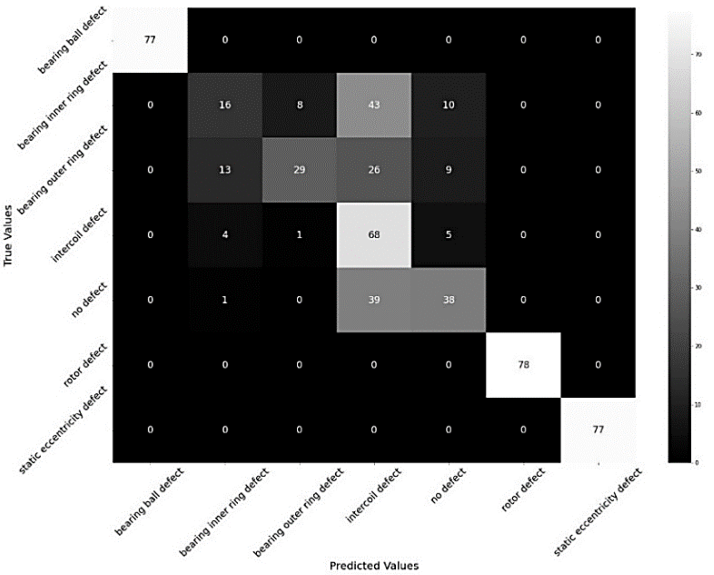


Figure 6. Error matrix

It is worth noting that the model is particularly over-trained on three classes: “bearing body defect” shown in Figure 7(c), “rotor bar failure” shown in Figure 7(h) and “static eccentricity” shown in Figure 7(i). The over-learning effect itself indicates that there may not be enough information in the data and it is easier for the model to remember certain values than to find relationships between them. Figure 8 shows the model's “confidence” distribution, ROC and RP curves for each class versus the other classes. The following correlation can be observed, the longer the duration of the input data, the better the model begins to distinguish the different defects from each other. It is worth noting that the use of time curve data also provides good results, close to the raw measurement results. It was also noticed that the network tends to over-train, the reason for this could be too implicit dependencies in the data, especially in the classes “bearing inner rolling surface defect” shown in Figure 7(c), “bearing outer rolling surface defect” shown in Figure 7(d) and “inter-turn short circuits” shown in Figure 7(f) as compared to data without defects as seen both in the error matrix and in the curve plots.

The difficulty in separating these classes can be explained by the insufficient information in the data, so further studies require more detailed elaboration of all features. Based on the results obtained, a “modified” set of classes was generated, Table 2 shows the metrics obtained on the test sample, as part of the new experiments. The best result was obtained when normalized voltage and current signals, of 3s duration, were applied. Figure 9 shows the f1-score variation plots on the training and validation sample; (a) F1-macro, (b) F1-micro, (c) F1-score bearing ball defect, (d) F1-score bearing ring defect, (e) F1-score no defect, (f) F1-score rotor defect, (g) F1-score static eccentricity defect, and (h) F1-weighted.

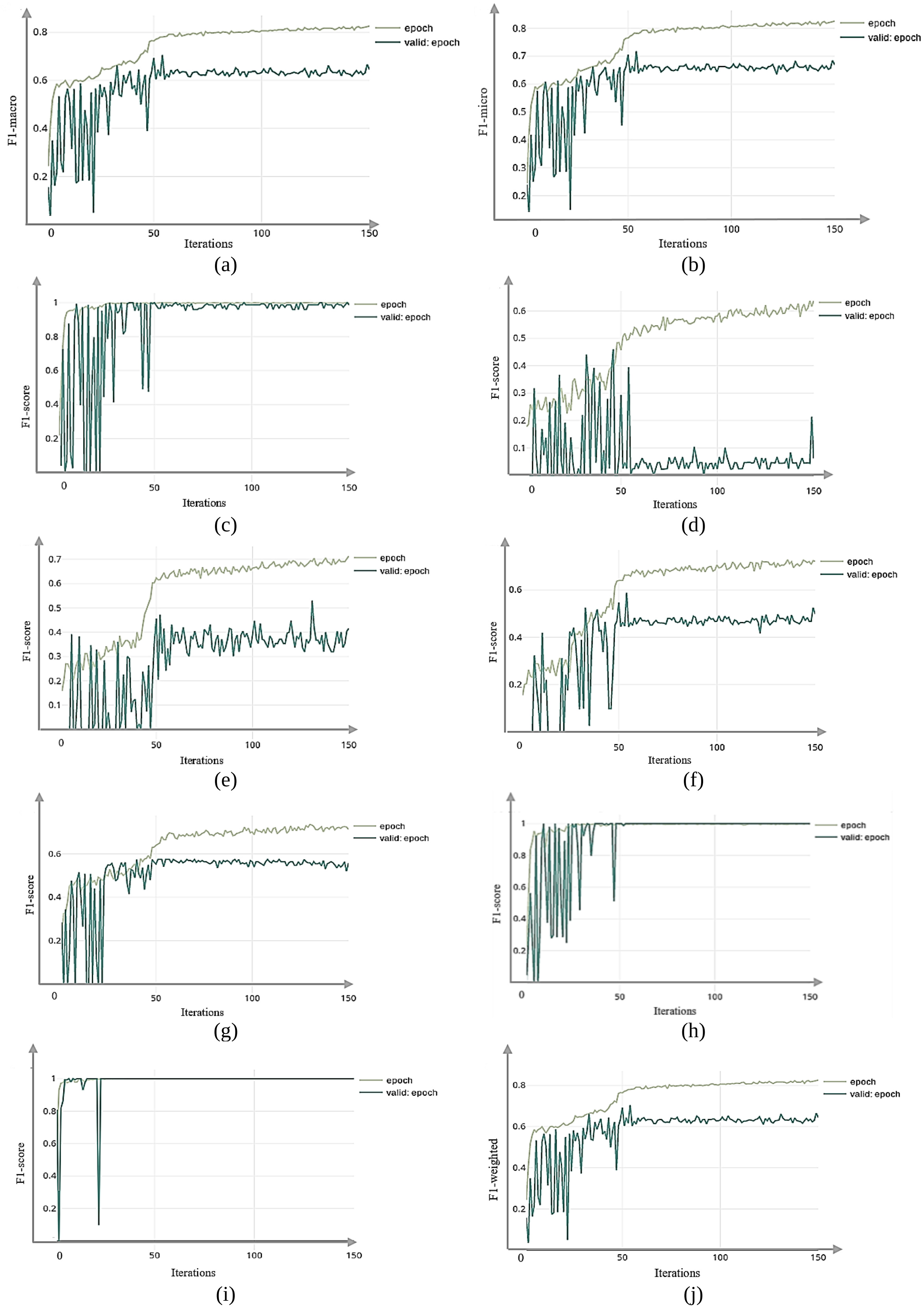


Figure 7. Graphs of f1-score change in the training and validation samples (a) F1-macro, (b) F1-micro, (c) F1-score bearing body defect, (d) F1-score bearing inner rolling surface defect, (e) F1-score bearing outer rolling surface defect, (f) F1-score inter-turn short circuits within one phase, (g) F1-score faulty motor, (h) F1-score rotor bar failure, (i) F1-score static eccentricity, and (j) F1 weighted

Table 2. Summary table of the results (modified set of faults of 5 classes)

Inputs	Duration (s)	Number of test intervals	Accuracy	F1 macro	Precision macro	Recall macro
Raw data	2	465	0.8	0.78	0.92	0.76
Normalized data			0.85	0.84	0.9	0.82
DQ			0.55	0.53	0.54	0.58
Normalized data	3	465	0.91	0.91	0.94	0.9

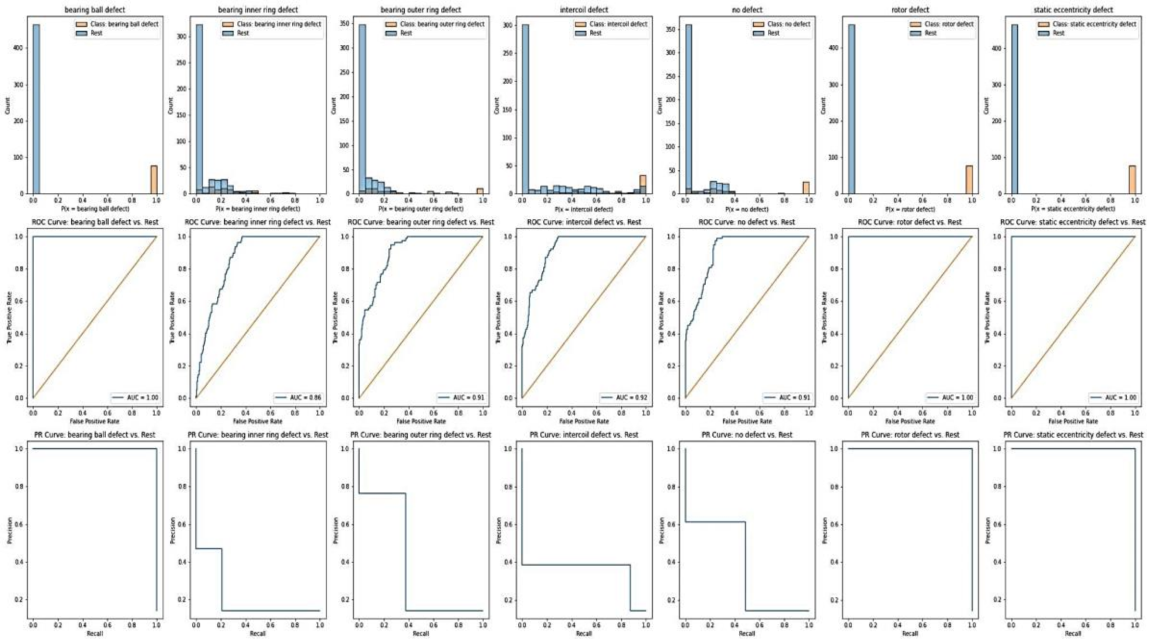


Figure 8. ROC and PR curves (defect vs other defects)

From the figures presented, it can be seen that this model is also likely to be over-trained. However, exclusion of the class "inter-turn short circuits" and merging of the classes "bearing inner rolling surface defect" and "bearing outer rolling surface defect" into "bearing surface defect" had a positive effect on the quality of the defect classification by the model. Figure 10 shows the error matrix obtained on the test sample. Figure 11 shows the distribution of the model "confidence", ROC and RP curves for each class against the other classes.

Using the modified configuration, it was possible to obtain better metrics for the model quality score, which confirms the hypothesis established above about the data of bearing inner rolling surface defect, bearing outer rolling surface defect and inter-turn short-circuiting. In this case, as with the full defect set, a similar relationship with the duration of the signals is seen, but normalization of the data showed better results than using raw values of voltages and currents.

As further research, it is planned:

- To increase the measurement frequency of the motor electrical signals. This can be achieved by optimizing the mathematical model and refining the physical test bench. By increasing the frequency of measurements, the effects of defects in the high-frequency part of the spectrum can become visible, which in turn can have a beneficial effect on the probability of correct classification of defects using neural networks.
- To change the approach to normalization of measurements. Although the use of data generalization in the form of the Park transform has not yielded any noticeable positive results, it is possible that data normalization could be useful to highlight more explicitly changes in the amplitudes of electrical signals. On the other hand, it may also have a negative effect on the accuracy of the classification, e.g. for non-defective changes in signal amplitudes, such as an increase in stator current with a rise in load. For this reason, it may be useful to normalize the value of each measurement independently.
- To use a longer duration of measurements for training. This would require a significant increase in computing power to process the same amount of input data. It also makes sense to diversify the training sample with a wider representation of each defect. This could involve varying the depth of the defect, introducing the defect into different motor phases where possible, and so on.

Consider other alternatives for the neural network architecture.

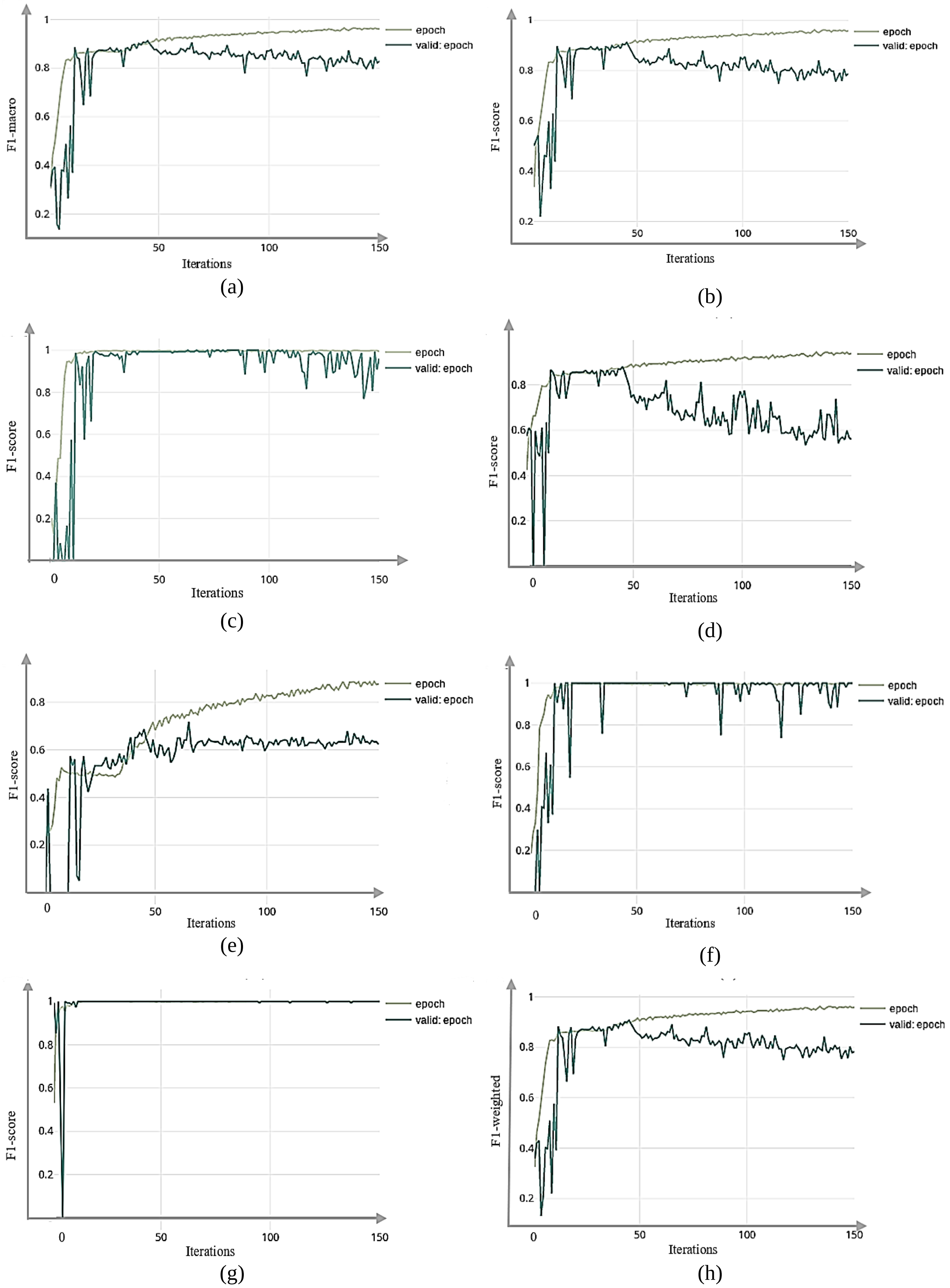


Figure 9. Graphs of f1-score variation on the training and validation sets (a) F1-macro, (b) F1-micro, (c) F1-score bearing ball defect, (d) F1-score bearing ring defect, (e) F1-score no defect, (f) F1-score rotor defect, (g) F1-score static eccentricity defect, and (h) F1-weighted

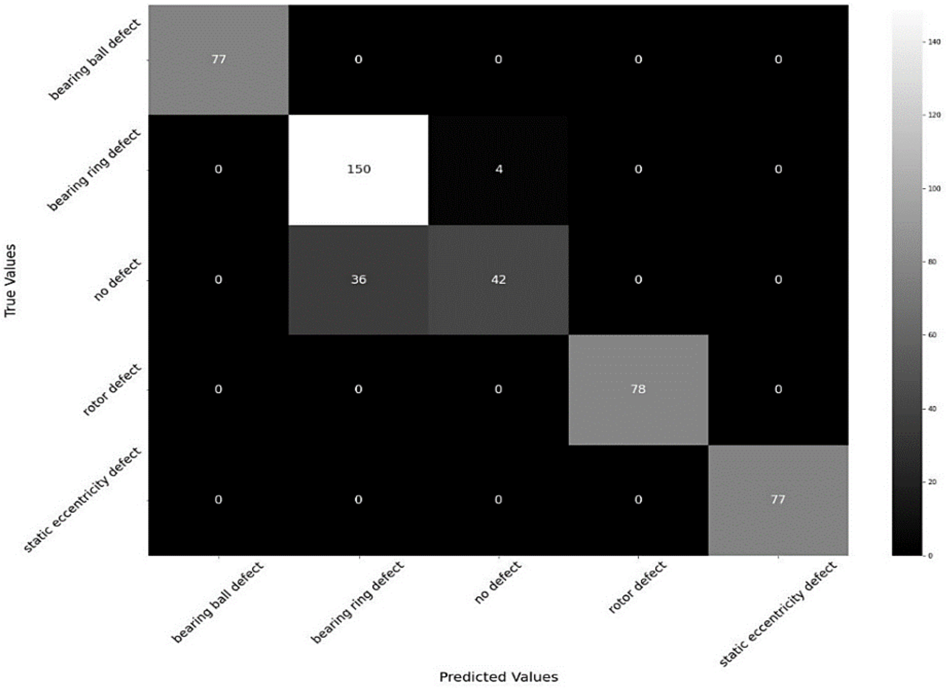


Figure 10. Error matrix

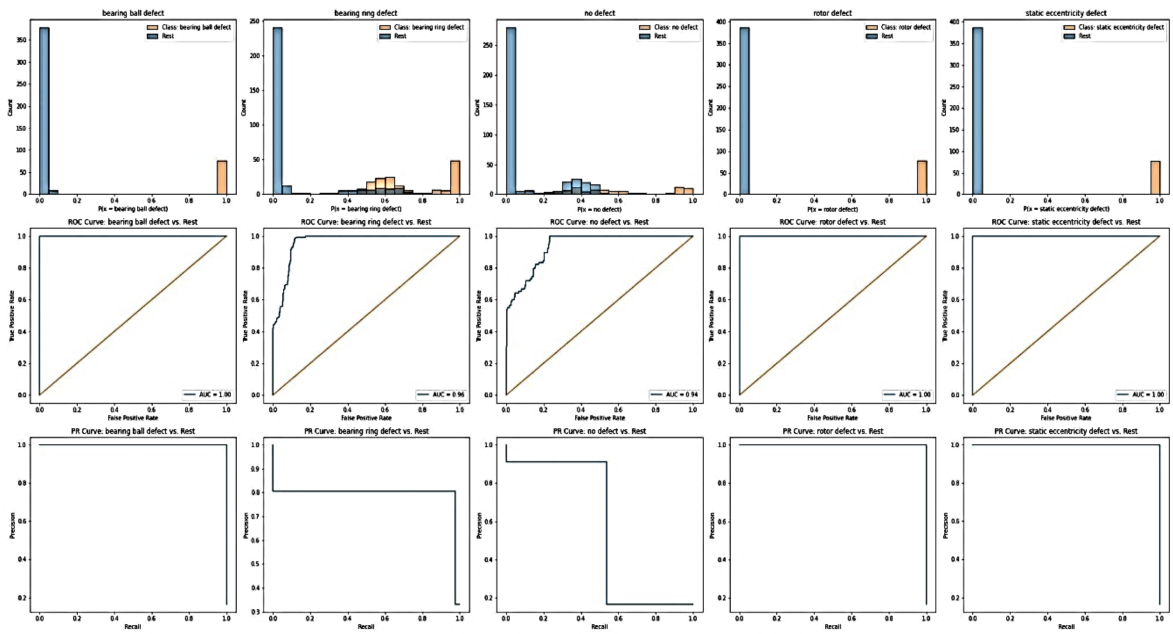


Figure 11. ROC and PR curves (defect vs other defects)

7. CONCLUSION

The study presents the results of development and setting of the neural network, which is able to detect and classify several classes of developing the SCIM defects (stator phase short circuits, destruction/deterioration of conductivity of rotor rods, air gap eccentricity, bearing defects). The research was purposely carried out under semi-natural conditions in order to verify the principal possibility of separating defects in an ideal measuring system. In this case, the task was complicated by the fact that the computer model obtained the spectral composition of stresses corresponding to physical measurements of the real network, and the depth of the defect changed insignificantly in a series of experiments. These studies indicate that positive results in solving the classification problem can be obtained by enlarging the defect classes according to the nature of origin (e.g., a group of bearing raceway defects). The only defect that is difficult to identify is stator insulation degradation. Positive learning effects were only obtained at low insulation resistances, which actually correspond to an emergency situation. The research has shaped the way forward and developed a prototype neural network that will be further tested on a physical prototype.

ACKNOWLEDGEMENTS

The research results presented in the article were obtained during the implementation of the initiative research and development project "Energy Efficient Electric Drive Systems of Industrial Facilities (NP/POPR- 4)" (Registration number: 121121700170-5), which is implemented in the framework of the Strategic Academic Leadership program "Priority 2030" at the St. Petersburg State Electrotechnical University.

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