Fault diagnosis of an induction motor using data fusion based on neural networks

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Abstract
In this paper, neural network-based data fusion is used to detect fault and isolate stator winding short circuit, outer bearing race, and broken rotor bar defects in an induction motor. In addition, the robustness of the proposed method against the disturbance introduced by the coupled pump’s unbalanced power source and dry running is investigated. First, three-phase current and voltage signals are separated by means of independent component analysis (ICA), then extracted features are combined by adopting neural networks, and finally, the system’s health condition is evaluated. Experimental results indicate that data fusion based on neural networks can evaluate with high reliability the system’s health condition and provide better robustness in the presence of disturbances.

1 | INTRODUCTION

Non-intrusive condition monitoring and fault diagnosis of electric motors with the goal of preventing harm and excessive repairs reduce the cost of maintenance and service. Various numerical approaches, including signal-based, model-based, artificial intelligence and data-fusion-based methods can easily use the current and voltage signals of the motor for fault diagnosis [1, 2]. Artificial neural network (ANN) approaches, known as smart methods, are increasingly used for automatic identification and troubleshooting of motor conditions, among these techniques [3]. The fusion of extracted features prevents any data redundancy of the original data. In [4, 5], using a linear weighted data combination, useful features from the stator’s electric current and vibration signals are derived, and then an induction motor misalignment fault is identified. Given the simplicity of this strategy, it suffers from weight initialisation difficulties. In [6], cross-correlation and spectral kurtosis are used to detect bearing fault in electric motors, and the features are separated by principle component analysis (PCA) and sent to K-nearest neighbours (KNN) for fusion. In [7–9], The current, vibration, optical, and accelerometer signals information have been combined in deep convolutional neural network (DCNN) for fault diagnosis, and PCA has also been used to learn features. In [10], the feature set is extracted using Fourier and Hilbert transformations from acoustic, vibration and current signals. Then the most useful features are selected through the adoption of principal component analysis, and the support-vector-machine (SVM) algorithm is proposed to detect bearing and misalignment failures in a motor. The problem with this PCA approach is that it concentrates on the input data and overlooks the output of the classifier. In addition, the method is slow during the training phase. In [11, 12], the efficacy of ANN and SVM in detecting bearing defects is investigated by comparing the vibration signal’s temporal characteristics, indicating the ANN’s high reliability. In [12], the efficiency of probabilistic neural network (PNN) neural network is investigated using the combination of entropy features to detect faults in high-dimensional systems. In [13], a fusion principle is used to identify the bearing and rotor faults of an induction motor. The Fourier transformation approach is used to find five different factors in its energy frequency spectra. The variables are used as the input to an radial basis function (RBF) neural network. To determine the well-being state of the system, the outputs of the RBF are combined and added to The D-S evidence theory. In [14], a technique was proposed to improve the reliability of stator winding fault detection by using three-phase stator current signals and using the D-S fusion theory. However, it did not perform well in The isolation of the faulty phase. In [15], a method is proposed for fault detection based on D_S theory and fuzzy rules. In [16], fuzzy integral theory was used at decision and feature levels for an induction motor of a laboratory electro pump...
system, and was able to detect faults with high reliability. However, the definition of fuzzy rules and the process of changing fuzzy system parameters, are often time-consuming, especially when the number of fuzzy rules is high in the system [17].

In this paper, preprocessing is considered to improve the accuracy of the evaluation of the sensor’s information compared to [7, 15]. According to [6], independent component analysis (ICA) is used to improve the performance of the separation process and to decrease the dependency and dimensionality of the input signals. Upon extracting the features, the entropy-based decision tree approach is used to select the appropriate features for a better performance compared to [7, 10], in which the PCA was used to select the appropriate features. These features are used as inputs to an RBF neural network to detect the existence of any fault and its severity. Since in addition to fault detection [18], fault isolation is also of great importance in condition monitoring of systems, so in the next step, the fault isolation of this system is investigated using neural networks. Also, the neural network’s performance in detecting the location of the stator winding short circuit is evaluated.

2  |  FAULT DIAGNOSIS METHODOLOGY

2.1  |  Independent component analysis

The sensors are used to gather environmental data. Such data can be incomplete, unclear, or conflicting due to the nature of the sensors, and this leads to a reduction in precision when determining the state of the device. This paper uses ICA to separate signals and reduce the overlap between these signals and eliminate some of the noise effects. ICA is a statistical method designed to identify the true data structure. In this multi-dimensional data technique, multiple unknown variables are considered to be a linear combination. Such variables are considered independent and non-Gaussian, and are understood to be independent components of the observed data. Here, being autonomous means that no knowledge about each other is exposed by independent components [19–21].

2.2  |  Feature selection

In order to detect faults in an induction motor using neural data fusion, first we should decide which features will adequately represent an induction motor disorder. Since changes in the current and voltage signals lead to variations in the torque of the system, and also statistical features are gained based on the torque, these kinds of features are considered in this paper. Actually, statistical data information in the time-domain is used in this paper to obtain the calculated signal characteristics. The functions are determined on the basis of the signal sample distribution. Since any difference in the signal state can result in a torque shift, most of these features are specified based on torque changes, and thus these features provide information to identify faults. Some of these features include mean, standard deviation, skewness, and kurtosis, given below:

\[
\text{Mean} = N^{-1} \sum_{i=1}^{N} x_i \\
\text{Std} = \left( N^{-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 \right)^{1/2} \\
\text{Skewness} = \left( N^{-1} \sum_{i=1}^{N} (x_i - \bar{x})^3 \right) \left( \sqrt{N^{-1} \sum_{i=1}^{N} (x_i - \bar{x})^2} \right)^{-3} \\
\text{Kurtosis} = \left( N^{-1} \sum_{i=1}^{N} (x_i - \bar{x})^4 \right) \left( N^{-1} \sum_{i=1}^{N} (x_i - \bar{x})^2 \right)^{-2}
\]

where \(x_i\) is the \(i\)th-sample in time domain and \(N\) is the total number of test samples. Standard deviation suggests signal distribution. In addition, kurtosis shows the signal smoothness as compared to normal distribution [16]. Another essential temporal function that shows the signal’s power content is the rms:

\[
rms = \sqrt{N^{-1} \sum_{i=1}^{N} x_i^2}
\]

It is widely used to monitor overall noise levels and is very efficient in detecting an imbalance in rotary machines [16].

Besides these features, some famous dimensionless parameters in time domain such as shape factor and crest factor can be pointed out, given by:

\[
\text{Shape factor} = \frac{x_{\text{rms}}}{\|x\|_\infty}
\]

\[
\text{Crest factor} = \frac{x_p}{x_{\text{rms}}}
\]

where \(x_{\text{rms}}\) is the effective value and \(x_p\) is the peak value of the signal. Crest factor can be used to detect a fault in gears [16].

In information theory entropy, indicates uncertainty. Entropy estimation is a two-step process: first, the histogram of samples is estimated, then the entropy is obtained from:

\[
\text{Entropy} = \ln \Delta - \sum_{i=1}^{P} (\times) \ln P(\times)
\]

where \(\Delta\) is the width of the sample histogram, \(\times\) is a discrete-time signal, and \(P(\times)\) is the total signal distribution [16].

Upon choosing the features, they are combined to assess the motor’s status using neural networks.

2.3  |  Neural networks for fault classification

Due to the great performance of radial basis function (RBF) neural network in predicting nonlinear functions and its ability
in adaptive learning, radial basis neural network is used (Figure 1) for nonlinear classification of faults [22]. In addition, an RBF is normally made of three layers that causes its faster performance than other neural networks. In this paper, the features that have been selected by the decision tree, have been considered as input to the proposed neural network. The kernel of the radial basis function is determined by the K-means algorithm, and the nearest neighbourhood algorithm is used to determine the radius of the kernels. The neural network proposed here has one hidden layer containing 40 neurons and the weights are initialised with a random distribution.

All the data are normalised before processing for better training and prediction capability. Therefore, a transformation on the input data has been carried out to scale the data in the \([-1, +1]\) range, as follows:

\[
X'_n = \frac{2(X_n - X_{\text{min}})}{X_{\text{max}} - X_{\text{min}}} - 1
\]  

(6)

where \(X_{\text{max}}, X_{\text{min}}\) are the maximum and the minimum of \(X_n\), respectively. Finally, 60% of the data is used for training, 20% for validation, and 20% for testing stages.

3 | EXPERIMENTAL SET-UP

In this study, a two-pole, 4 KW induction motor is used. Also, as shown in Figure 2, a centrifugal pump is connected as the load. According to Figure 3, the stator winding of the induction motor is opened to introduce a short-circuit defect scenario to test the stator winding faults. To perform this task, some of the windings are carefully taken out of the motor while connected to the main winding. As a quick detection of winding fault is crucial to prevent insulator loss due to overheating, a low percentage of short-circuit is made as the winding defect. Moreover, One of the motor bearings is removed from the rotor to establish bearing faults, and then a small hole is created on the outer bearing race as shown in Figure 4. Also, according to Figure 5, a rotor fault scenario is simulated by making a hole on one of the rotor bars. In this experiment, dry-running of the centrifugal pump is...
TABLE 1  Average accuracy of the proposed method for normal and stator winding short circuit conditions

| Health condition | Proposed method results | Fusion of the three-phase current signal characteristics | Fusion of the selected features of three-phase current signal using decision tree | Fusion of the selected features of three-phase current and voltage signals using decision tree |
|------------------|-------------------------|--------------------------------------------------------|--------------------------------------------------------------------------------|--------------------------------------------------------------------------------|
|                  |                         | Normal       | Faulty     | Normal       | Faulty     | Normal       | Faulty     |
| ICA signals      | Normal                  | 45.9         | 54.1       | 52.31        | 47.69      | 96.39        | 3.61       |
|                  | Faulty                  | 12.44        | 87.56      | 7.255        | 92.745     | 4.05         | 95.55      |
| Sensors signals  | Normal                  | 29.4         | 70.6       | 51.76        | 49.24      | 88.81        | 11.19      |
|                  | Faulty                  | 36.74        | 63.26      | 24.64        | 75.36      | 19.4         | 80.6       |

TABLE 2  Average accuracy of the proposed method for normal and bearing fault conditions

| Health condition | Proposed method results | Extracted features of three-phase current | Selected feature of three-phase current |
|------------------|-------------------------|------------------------------------------|----------------------------------------|
|                  |                         | Normal         | Bearing fault  | Normal         | Bearing fault  |
| ICA signals      | Normal                  | 75.37         | 24.63         | 90.99         | 9.013          |
|                  | Bearing fault           | 11.32         | 88.68         | 6.19          | 93.81          |
| Sensors signals  | Normal                  | 65.28         | 34.72         | 91.08         | 8.92           |
|                  | Bearing fault           | 17.38         | 82.62         | 10.58         | 89.42          |

studied to test the efficiency of the algorithm in detecting the load-related faults.

Also, the LA-55 P/SPI and LV25-P sensors are used to monitor three-phase current and voltage signals, and the Advantech PCI-1711 data acquisition card is used as a data storage device for the PC. Data with sampling frequency of 10 KHz was registered for 10 s. This was collected 20 times (during 20 experiments) to obtain richer data.

Each set of data includes bearing-related signals, unbalanced power source, broken rotor bar, short-circuit stator winding, and dry-running faults, as well as one healthy condition. Using decision trees, the dimensionality of the characteristic vectors is reduced. This can help in selecting more useful features for classifying faults by neural network.

4  EXPERIMENTAL RESULTS

4.1  Fault detection

The features described in 2-2 are extracted from the current tri-phase signals. These features are used as the inputs to the RBF neural network to determine the system’s health status among the conditions of normal, stator winding short circuit, bearing defect, and broken rotor bar.

According to Table 1, it is observed that the accuracy obtained by integrating the three-phase current data for fault detection is not reliable. This problem is due to the multitude of features extracted, and hence the decision tree is proposed to reduce the dimensionality for a better feature selection.

Therefore, in stator winding short circuit detection, mean of three phases, skewness of the second phase, and rms of the second and third phases of the pre-processed tri-phase current signals have been selected. Results show that this strategy provides good accuracy but the reliability is still low in detecting faults. Since the voltage signal also changes due to faults, the time features mentioned are extracted from the voltage signal, and combined with the current features, The quality of the neural network-based fault detection strategy with the selected features, mean of the first and second phases, skewness of the second and third phases, shape factor of the first phase of current signals, and entropy of the third phase of voltage signals is evaluated by the decision tree, which provides better accuracy and enhanced reliability.

In order to assess the performance of the proposed method, bearing fault and broken rotor bar fault detection are evaluated with this method as well.

As shown in Table 2, the proposed method in both case is able to determine the faulty condition with good accuracies (88.68% and 93.81%). However, 75.37% accuracy for the normal condition using extracted features is not suitable for fault detection purposes. Therefore, adopting selected features, mean of the second and third phases, rms of the third phase, skewness of the second phase, crest factor, and entropy of the first phase of pre-processed three-phase current signals by decision tree increases the accuracy to almost 91% which is preferable compared to the former approach.
TABLE 3  Average accuracy of the proposed method for normal and rotor bar fault conditions

| Health condition | Proposed method results |
|------------------|-------------------------|
|                  | Extracted features of three-phase current | Selected feature of three-phase current |
|                  | Normal | Rotor bar fault | Normal | Rotor bar fault |
| ICA signals      |        |                 |        |                 |
| Normal           | 73.24  | 26.76           | 85.45  | 14.55           |
| Rotor bar fault  | 23.91  | 76.09           | 12.11  | 87.89           |
| Sensor signals   |        |                 |        |                 |
| Normal           | 69.68  | 30.32           | 80.31  | 19.69           |
| Rotor bar fault  | 27.63  | 72.27           | 13.29  | 86.71           |

According to Table 3, extracted features fusion shows 74.66% accuracy in determining the health condition, while 86.67% accuracy can be obtained using the selected features approach. Actually, mean of the first and second phases, rms of the first and second phases, and skewness of the second phase of pre-processed current signals have been selected to evaluate the Rotor bar fault detection.

The fault detection algorithm performed well by combining the information extracted from the independent-component-analysis signals compared to those extracted from the sensor signals. To find out why the reason, sensor signals and independent-component-analysis signals are compared to an ideal source signal as shown in Figure 6. Actually, the ICA method has been applied to three phases of current and voltage signals to reduce their overlap and noise effect.

It can be seen from these figures that the output of the three-phase signals of the ICA is quite similar to the ideal current source (Figure 7).

According to Figure 6(b) The signals collected by the sensors are overlapped and also affected by the noise, while these effects are considerably reduced using independent component analysis, as shown in Figure 6(c). This comparison can be seen more clearly in Figure 7.
4.2 | Fault isolation

So far, the fault detection of the induction motor was investigated which can be regarded as a classification problem with two classes, namely normal and faulty conditions, and the performance of two neural network-based methods were evaluated with extracted and selected features. In this section, the ability of the neural network is investigated for fault isolation using a fusion of current and voltage signal characteristics with taking into consideration the healthy state of the motor, the short-circuit stator winding fault of 8% and 12.5%, the bearing fault, and the broken rotor bar in a five-class problem, as shown in Table 4.

According to Table 5, the proposed neural network is capable of isolating different conditions of the system but the results for the normal condition and broken rotor bar are not so good, This leads to an average 70.25% accuracy for this method. Accordingly, selected features, mean of the first and third phases, skewness of the second phase, the shape factor of the first phase, and entropy of the second and third phases, fusion is employed to enhance the reliability of fault isolation; results are shown in Table 6.

It can be seen that The normal and broken rotor bar isolation accuracies are improved, and This has increased the average accuracy to 85.78%. Yet, broken rotor bar accuracy is not satisfactory for the fault isolation problem. Therefore, current and voltage selected features fusion are proposed and evaluated in the following.

According to Table 7, the neural network based on the fusion of selected features, mean of the first and third phases, skewness of the second phase, crest factor of the second phase of pre-processed current signals, and entropy of the first phase, and rms of the third phase of pre-processed voltage signals, has provided an average accuracy of 88% for fault isolation when both current and voltage signals are used.

Since the performance of the fault isolation is highly influenced by disturbances, the performance of the proposed method is evaluated in the presence of disturbances.

4.3 | Evaluation of the proposed method in presence of disturbance

The induction motor introduced earlier is connected to an electro-pump according to Figure 2. Pump dry running is one of the common faults faced in electro-pumps and reduces
the performance of the system. The intent of this study is to detect and isolate potential faults in the induction motor of an electro pump system, therefore, the effect of a potential pump dry running is taken into account in the proposed fault detection method. To introduce this disturbance to the system, purposely a valve along the water pump piping direction was closed and reopened. Also, an unbalanced input power source is taken into account as another disturbance source. Variac is utilised to introduce this disturbance to the system as shown in Figure 8. Due to the fact that the power source unbalances of 2% to 4% is common in the practical state, in order to create such a disturbance, the effective value of the first and third phases are set at 220 volts and the effective value of the second phase voltage at 215 volts, thus simulating a 2/72% unbalance.

After creating disturbances, independent component analysis for preprocessing the collected current and voltage signals of the induction motor in the presence of disturbances is applied to extract the temporal characteristics of the signals in the simultaneous presence of induction motor faults and disturbance. Since a large number of features cause computational problems and decrease the accuracy of the fault detection system, a decision tree is exploited for dimensionality reduction. As a result of using the decision tree to select the best features, mean of the first phase and skewness of the third phase of pre-processed current signals; and Std of the second and third phases, skewness of the first and third phases, and entropy of the first phase of pre-processed voltage signals are selected to evaluate the proposed method in presence of disturbance. seven classes are taken into account for The fault isolation problem, according to Table 8, and the performance of neural networks with selected features are evaluated.

According to Table 9, the neural network can distinguish faults with an average accuracy of 98% with the fusion of selected current-and-voltage features, which suggests great robustness against disturbance.

### Table 8: Classification of electro-pump induction motor faults

| Health condition                                      | Class index |
|------------------------------------------------------|-------------|
| Normal (free)                                        | 1           |
| Stator winding short circuit (8%)                    | 2           |
| Stator winding short circuit (12.5%)                 | 3           |
| Bearing defect                                       | 4           |
| Broken rotor bar                                     | 5           |
| Pump dry running                                     | 6           |
| Unbalanced power source                              | 7           |

### Table 9: Fault and disturbance isolation using selected current and voltage features

| Faulty phase isolation of a stator winding          |
|----------------------------------------------------|
| 4.4                                               |

As the short circuit of the motor windings is a fault that must be diagnosed at low percentages, the reliability of the proposed method to detect the exact location of the fault in the stator winding is investigated.

The main effect of a winding fault of the stator is naturally the change in the associated current signal. The identification and isolation of this fault from other defects have been addressed in previous sections.

In this section, considering a short-circuit in the stator winding phase-a as shown in Figure 9, detection of the faulty phase is investigated using neural networks by fusion of the characteristics extracted from the current three-phase stator signals.

The neural-network-based fusion of the extracted time features of the three-phase currents are evaluated in the healthy and faulty states, and the performance of the neural networks is evaluated by considering six classes for classification of healthy/faulty phases according to Table 10.

The fault detection results are shown in Table 11.
Since the three-phase current signals are segregated using the ICA algorithm, when fusion is suggested, the neural network can detect the defective state with 81.66% reliability.

5 | CONCLUSION

In this paper fault detection and Isolation of an induction motor are investigated using extracted features fusion with neural networks, and selected features using decision tree from current and voltage signals. Fault detection system with feature fusion could not present acceptable performance, however, using selected feature fusion by decision tree increased accuracy to 95% which is quite promising for fault detection application. The presented method was able to detect bearing fault and broken rotor bar with an average accuracy of 90% and 86% respectively.

Because of the high accuracy of the proposed method, this method was adopted for fault isolation. Using current extracted features, the accuracy was obtained 75.25%, while using current selected features and current-and-voltage selected features, the accuracy increased to 85.78% and 88%, respectively. Moreover, the robustness of the proposed method in the presence of pump dry-running and the unbalanced power source was investigated and 98% accuracy was achieved. This method was used to detect stator winding short-circuit fault, and 81.66% accuracy was achieved, indicating a suitable accuracy in locating the fault in addition to fault detection and isolation.

In this paper, data preprocessing is proposed to improve the accuracy of the evaluation of the sensor’s information compared to [7, 14], which has led to the improvement of the performance of the fault diagnosis system in monitoring the condition of the induction motor. (Sections 1–4, Tables 1–3). Also, as a result of signal preprocessing, the fault detection system has performed with high reliability in the separation of the faulty phase of the stator windings, compared to the performance presented in [13]. Also, in this research compared to [17], in addition to investigating the fault detection in an induction motor, the performance of the proposed method in fault separation, as well as the fault phase detection capability has been investigated.

In this paper, the performance of the proposed method has been investigated at a constant load. Hence examining load range for the centrifugal pump and induction motor fault conditions in the performance of the proposed method can be investigated as an innovation for developing the results of this study. In spite of the high reliability of neural networks in fault diagnosing with the fusion of current-and-voltage-signals features, this method is limited to using expert humans to extract features from signals. This limitation can be investigated by using deep neural networks. Moreover, The neural network-based method proposed in this paper is usually known as a data-based method. Although the neural network has to be trained for each system, the trained neural network can be used for other cases by using the transfer learning method.

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