Received February 11, 2019, accepted February 27, 2019, date of publication March 11, 2019, date of current version March 26, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2904238

Investigation of Combined Electrical Modalities for Fault Diagnosis on a Wound-Rotor Induction Generator

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This work was supported in part by the Eskom Tertiary Education Scheme Program and in part by the University of Johannesburg URC Research Grant.

ABSTRACT An online method for fault diagnosis on a wound rotor induction generator using stator voltage and current, and rotor current are investigated. The diagnostic method comprises processing of the generators signals and classification of the machine's condition according to healthy or specific fault type. The signal processing phase of the intelligent fault diagnosis process extracts features, which are frequency-based, interrelated to specific fault modes, i.e., stator winding, rotor winding, and brush faults. Finite element modeling of a wound-rotor induction generator is carried out under normal and different fault conditions for the purpose of conducting preliminary design and testing of the classification system. An experimental setup is then used to validate the computational results and verify the diagnostic method. The results indicate that the stator voltage, stator current, and rotor current modalities exhibit patterned sensitivities to the investigated faults. It is found that the classifier works well with a large number of features offered by the combination of these modalities yielding a best overall diagnostic accuracy of 99% in an experimental setting.

INDEX TERMS Condition monitoring, wound-rotor induction generator, fault diagnosis, classification.

I. INTRODUCTION

Wound-rotor induction generators (WRIG) are simple, robust and can be driven at varying speeds and still provide a stable supply. Furthermore, WRIGs allow dynamic rotor resistance control which improves output power harnessing over a wide range of speeds - hence their suitability for use in wind turbines [1]. However, in some applications, excessive power or stability problems in the system may necessitate standalone operation of the WRIG. In these cases, WRIGs can be operated as an isolated generator with capacitors to supply reactive power required by the generator and loads [2]. Despite the aforementioned relatively robust nature of this machine, there are still a variety of faults that do occur in practice. Recently, more attention is being given to research of WRIG condition monitoring methods [3]. Abnormal behaviours in WRIGs under faulty conditions may cause damage to the turbine and interconnected equipment, further resulting in production loss due to unscheduled repairs [4]. The ability to accurately diagnose different types of faults is therefore an ongoing research challenge.

The research presented in this paper aims at developing an online method for diagnosis of stator and rotor winding inter-turn short-circuit, and brush faults on a WRIG. Machine learning classifiers are adopted to identify these faults based on features extracted from multiple electrical signals - i.e. stator voltage and current, and rotor current signals. For the classification, a comparative analysis of Bayesian classification, Artificial Neural Networks (ANN) and Support Vector Machines (SVM) is carried out. The harmonics of these signals are also analysed for patterned sensitivities to the different investigated faults to serve as suitable features. First, modelling of the WRIG under healthy and fault conditions is performed. These results are then validated experimentally by carrying out real measurements on a WRIG. The results from the model simulation and experimental results are then used to train and test the classification system. To the best of the authors' knowledge, this type of multiple fault diagnosis investigation, using multiple modalities, on WRIGs has not yet been presented and will definitely enhance the incipient fault detectability and identification procedure on these machines. In the subsequent section, different faults, measurement modes, and methods of fault detection and diagnosis relevant to WRIGs are briefly reviewed.

The associate editor coordinating the review of this manuscript and approving it for publication was Ming Luo.

Section III describes the methodology, modelling, experimental configuration, and development of the fault classification system. This is followed by validation of the numerical results with experimental results and testing of the fault classification system in Section IV. Finally, a brief conclusion and summary of the research is given.

II. BACKGROUND

In general, predictive maintenance has two major objectives, that is, to detect and diagnose problems - at an incipient stage - through suitable techniques and then to act accordingly to avoid fault progression and unplanned downtime [5]. While application of various techniques on induction motors have received significant attention, there is unsubstantial research pertaining to application of the same on the WRIG. As with most research areas of electrical machines – such as design and control - condition monitoring is also evolving into the fourth industrial revolution. There is a greater need for accurate and reliable condition monitoring and analytics systems to be developed. Thus, intelligent systems have to be built around the aforementioned existing techniques, through data fusion of machine signals [3], to provide incipient diagnosis and detectability of multiple fault mechanisms.

A. INDUCTION MACHINE FAULTS

Several studies have been carried out on induction motors to categorise types of fault as a ratio of total fault occurrences. The most common problems in induction machines are interturn faults on stator and rotor windings, broken rotor bars and end rings, static and dynamic air-gap irregularities, bowed shaft, bearings misalignment and mechanical imbalances as discussed in [6]. Current spectrum analysis is the most popular fault detection method used on induction machines and has been covered in many works as discussed in [7]. This method of fault detection can employ different signal processing techniques. The signal processing techniques that are most commonly used for this purpose are the frequency domain Fast Fourier Transform (FFT), time-frequency domain Short-Term Fourier Transform (STFT) and wavelet transform [8].

TABLE 1. Summary of types of faults occurring on induction machines.

Fault type	Percentage of total fault occurrences
Bearing	40%
Stator	35%
Rotor	10%
Eccentricity	10%
Other	5%

According to the IEEE standard 493-1997, the categorisation of faults occurring on induction motors in practice are presented in Table 1 [9]. A report on the survey conducted by the Electric Power Research Institute (EPRI) also provides comparable results [10]. Bearing faults account for the majority of faults occurring on induction machines. Brush or slip-ring faults also feature as a major fault category besides bearing and winding faults. Although these statistics provide some insight into the frequency of types of faults experienced in practice, it should be noted that most faults are interlinked through fault mechanisms. For instance, misalignment or eccentricity can progressively lead to bearing faults or failure. In view of the cascading nature of faults, it should be highlighted that this categorisation of fault types is dependent on mode and time of discovery of the fault. Simply put, this categorisation of fault occurrence is not necessarily indicative of root causes. Therefore, early diagnosis of fault is crucial in halting fault progression and avoiding the cascading effects thereof.

In practice, WRIGs exhibit a variety of faults of both mechanical and electrical categories. Stator winding interturn faults arise due to insulation deterioration and these faults result in the short-circuiting of the phase winding [10]. Rotor winding inter-turn faults or brush failure are due to insulation failure, noise and vibration. These faults can result in unbalanced resistances and magnetic forces leading to further fault progression [4], [11]. Eccentricity faults occur in three forms namely static, dynamic and mixed. These faults are due to airgap irregularities and may lead to unbalanced magnetic pull and even shaft bending [12], [13]. Misalignment and unbalanced magnetic pull result in bearing faults which eventually lead to increased vibration and noise levels [14].

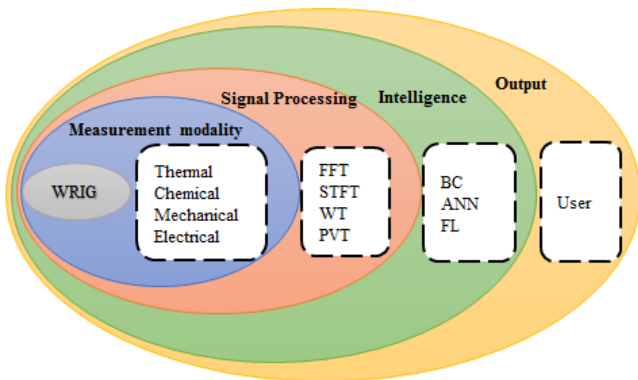

FIGURE 1. Overview of typical modern condition monitoring architecture.

B. CONDITION MONITORING SYSTEM ARCHITECTURE

In general, modern condition monitoring systems for electrical machines typically follow a layered architecture comprising subsystems that are specific to maintenance requirements of the application. Figure 1 gives a general overview of this typical layered architecture of a fault diagnosis system. The measurement modality subsystem in the architecture represents the parameter or signal, either through direct or indirect measurement or inference, that could be inter alia thermal, chemical, mechanical, electrical etc. Thereafter, processing is employed to extract features of the parameter or signal form the first layer and could be in the form of transforms or simple threshold or range checking. Some common examples of these processing methods are given in Figure 1. Modern fault diagnosis systems are now employing an intelligence layer which uses features obtained from the preceding layer to accurately infer or predict the condition of the machine. The intelligence provides the opportunity for data fusion of multiple signals and embedding analytics thereby enabling reliable incipient fault diagnosis. The presented fault diagnosis system follows this modern architecture.

C. MEASUREMENT MODALITY

The measurement modality component is the principal source of information used to make an inference about the state of an electrical machine. A single condition-monitoring system may use a combination of different methods of measurements. The suitability of a specific measurement modality depends on the required information and application of the machine. The measurement modality's sensitivity to the fault condition ultimately determines the early fault detection ability of a condition monitoring system. Condition monitoring via chemical-based techniques are used for detecting insulation deterioration resulting from high temperatures thereby yielding a number of chemical products in gas, liquid and/or solid states. These chemical products can be detected by these techniques to determine early signs of insulation failure [15]. Thermal methods typically employ three different approaches namely embedded temperature detectors for local measurements, thermography for hot-spot detection [16] and temperature measurement of coolant fluids [17]. Mechanical methods usually comprises monitoring of vibration, noise discharges, torsional oscillation and shock pulses. The interrelated faults are eccentricity and bearing misalignment that will in turn bring about vibration [18]. Electrical measurement modalities include flux, current, voltage and power which are commonly used for online monitoring [19]. More recently, multiple modalities have been used together to perform condition monitoring such as presented in [20], which utilises electrical and mechanical measurement modalities of a WRIG to diagnose problems with the drivetrain gearbox.

D. SIGNAL PROCESSING TECHNIQUES

The signal processing phase of the condition monitoring system extracts the features or markers from the parameter/s or signal/s. The objective is to extract features which are related to specific generator fault modes. A feature extraction technique is needed for signal processing of recorded time-series signals to acquire appropriate feature parameters. These techniques make it feasible to detect changes in signals arising from fault mechanisms. Specific dissimilarities between signals under normal and fault scenarios indicate changes in the machine's condition. There are some commonly used signal processing techniques, mostly with the aim of generating amplitudes of the frequency components from the measured signatures. The Fast Fourier Transform (FFT) is the most popular method used for frequency analysis of current signals forming the basis of online condition monitoring techniques as explained in [21]. FFT techniques can be used to give information about different faults and can detect low level fault signatures. For steady-state analysis where the load is constant, the FFT technique is most appropriate. Researchers have discovered that the FFT technique does not work well when applied under variable loads, dynamic (transients) conditions and no-load conditions. Only the frequency statistics can be provided with FFT technique, but the time statistics cannot be provided [22].

Short-Term Fourier Transform (STFT) based techniques are time-frequency domain based. STFT techniques are applied to overcome some of the disadvantages of FFT technique. The STFT reveals time information and can be applied under dynamic conditions, and also provides time-frequency domain characteristics simultaneously thereby enabling 3 dimensional analysis as discussed in [23]. However, the STFT technique does pose the disadvantage of poor frequency resolution. Some research has attempted to resolve the problem of poor frequency resolution by using the alternative Wavelet transform (WT). WT is also a time-frequency domain method which uses narrow windows for high frequency components. The technique decomposes the signal into a set of non-sinusoidal waveforms and has been applied by for motor current signature analysis (MCSA) [24], [25]. Wavelet transforms can be applied for time-frequency or time-scale domain with multi-resolution as described in [26]. However, with wavelet techniques, the scale domain is referred to as the inverted frequency rather than the frequency. Variable resolution can also be achieved which is particularly useful at higher frequencies as explained in [27].

Park's Vector Transformation (PVT) techniques require the current to be monitored on all three-phases. It can be generated from the symmetrical three-phase current system and, after the transformation, results in Park's vector components i_d and i_q as described in [28]. This method can also be generated using voltage rather than current, however this measurement modality has the disadvantage that it is not as sensitive to torque fluctuations [29]. There has also been efforts to apply more robust signal feature extraction methods for condition monitoring on induction motors such as presented in [30] which uses Multiple Signal Classification technique.

E. INTELLIGENCE METHODS

In general, machine learning methods have been employed to automate the decision making stage of diagnostic systems to indicate the fault condition, and/or determine root causes [13]. Some examples of these techniques include inter alia Bayesian classification, artificial neural networks (ANN), fuzzy logic, decision trees, support vector machines, K-means clustering etc.

Bayesian classification is a commonly used machine learning technique that applies logical calculus for making decisions under uncertainty. The advantages of Bayesian classification is its strong theoretical foundation and mathematical computation to make predictions, which makes it more transparent and easily accessible relative to other similar techniques. Furthermore, it may be used together with other classifiers to improve accuracy and performance for prediction [31], [32]. Bayesian classification employs Bayes theorem which is an algebraic model from fundamental of probability of hypothesis (H) and evidence (E) is expressed in (1):

$$P(H|E) = \frac{P(E|H) \times P(H)}{P(E)} \tag{1}$$

where $P(H)$ and $P(H|E)$ are the prior and posterior probabilities respectively, $P(E|H)$ and $P(E)$ are the likelihood and evidence, respectively. A key benefit of this type of classifier in relation to others is that if an instance is predicted to fall into a certain fault category, it offers the additional quantitative measure of the classification [33]. The classifier yields a probability associated with each instance thereby giving an indication of accuracy as well as if there is a need to improve it through additional learning instances. The Naïve Bayes classifier (NBC) is efficient in terms of time, CPU usage and memory. NBC performs well even with small training sets, applies strong independence assumptions through use of an independent feature model [34]. Due to these advantages, the presented work applies Bayesian classification for the intelligence stage of the fault diagnosis method.

Artificial neural networks (ANN) are becoming more popular in condition monitoring and is essentially a computational intelligence method with an ability to accumulate and assemble data processing. These networks comprise processing units known as neurons which are arranged inside in a structure similar to human brain processes. This method also needs training for all possible operating conditions of the machine [13], [35]. An example of application of ANN is given [36], where the frequency components of the current data are extracted by a pre-processor and are classified into four classifications based on importance level with the rule-based frequency filter. Reference [37] is another recent example of application of ANN in condition monitoring. SVM has also been shown to perform well for intelligent fault classification on a wind turbine drivetrain gearbox in [38] and [39]. The performance of ANN and SVM is also tested - together with NBC - in the presented work for the purpose of intelligent fault classification on the WRIG. Fuzzy logic has also been applied for decision making in machine condition monitoring [40] and basically consists of membership functions, which show the level of possibility that an object is an element of a certain class. Fuzzy logic is particularly useful where system information is limited or unclear.

III. METHODOLOGY

A. OVERVIEW

Typically, the success of spectrum analysis in condition monitoring depends on clear identification of variation trends in specific spectrum components. In the case where these trends occur as variation patterns across multiple components of a signal spectrum, it becomes challenging to detect or analyse. It is even more difficult to detect these patterns if they occur across multiple components of different signals' spectra. The presented methodology firstly investigates the presence of such variation patterns in multiple signals of a WRIG under different conditions through use of a finite element model and an experimental setup. Thereafter, a classification system is developed and tested to verify if those patterns can be learned so that new unknown instances of the measured signals can be used to predict the condition of the WRIG.

TABLE 2. Specifications of experimental induction machine.

Description	Value
Rated power	1 kW
Frequency	50 Hz
Power factor	0.8
Synchronous speed	1500 rpm
Rated voltage	380 V
Number of poles	4
Number of phases	3
Number of stator slots	36
Number of rotor slots	24
Stator outer diameter	140 mm
Stator inner diameter	103 mm
Rotor outer diameter	102.2 mm
Rotor inner diameter	32 mm
Length	90 mm

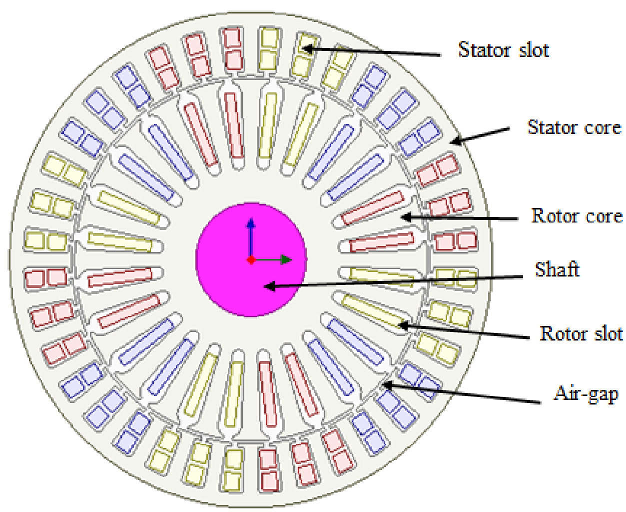

FIGURE 2. Finite element model geometry of wound-rotor induction generator used in investigation.

B. MACHINE AND FAULT MODELLING

The specifications of the WRIG machine used in the investigation is given in Table 2. The machine model was created using ANSYS Maxwell. The geometry of the WRIG model is shown in Fig. 2.

The faults considered are inter-turn short circuits on the stator windings and the rotor windings, and brush faults. These faults are considered separately and therefore multiple models were created - i.e. healthy, stator fault, rotor fault and brush fault. The WRIG machine has three phase windings on both the rotor and stator. Faults are modelled through short-circuiting the turns of one of the phase coils. Three and six turns are short-circuited in each case to incorporate the different levels of the same fault type. Figure 3 shows the geometric model indicating the points of faults.

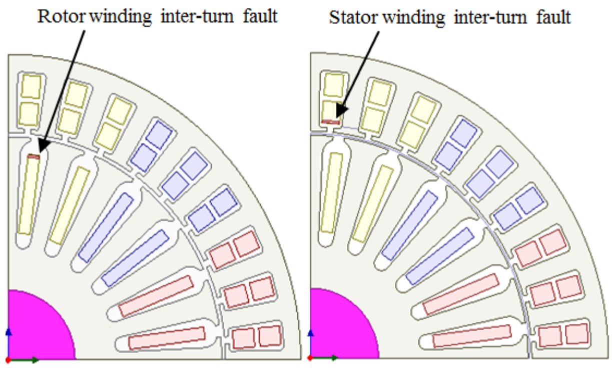

FIGURE 3. Rotor and stator winding faults as modelled on machine geometry.

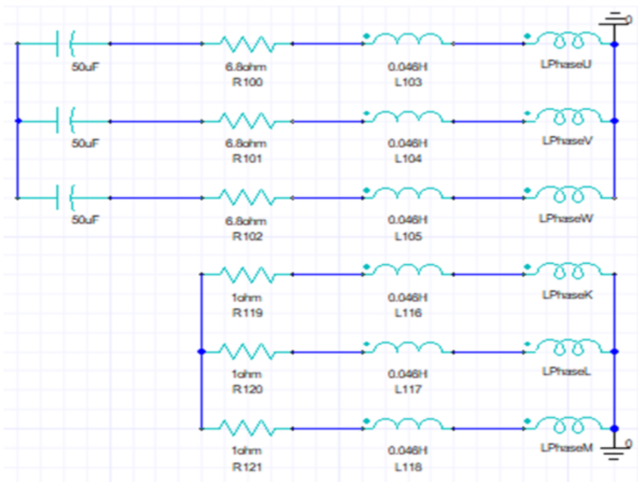

FIGURE 4. External circuit model of machine.

The simulation model includes an external circuit of a self-excited wound-rotor induction generator. The circuit model is used to build the external circuit for the generator and modify the electrical parameters accordingly with respect to each fault scenario. The brush fault is simulated by connecting a 0.5 Ω a resistor in series with the brush rotor external circuit as presented by Fig. 4 to create an imbalance that often occurs in practice. When repeating simulations to obtain different instances of each condition, the value of the capacitor excitation was randomly varied by $\pm 2\%$ for the purpose of creating a normal distribution of several different data instances under each condition. The machine is operated at synchronous speed for the simulation scenarios - i.e. 1500 rpm.

C. EXPERIMENTAL CONFIGURATION, FAULT IMPLEMENTATION AND TESTING

The laboratory setup used the in the investigation is presented in Fig. 5. It consists of a three-phase, 1kW, 380V, 4-pole wound-rotor induction machine, capacitor bank, circuit breakers, prime mover (larger induction machine and variable speed drive), variable resistors, voltage and current transducers, shaft encoder and data acquisition card which enables real-time interface with a computer.

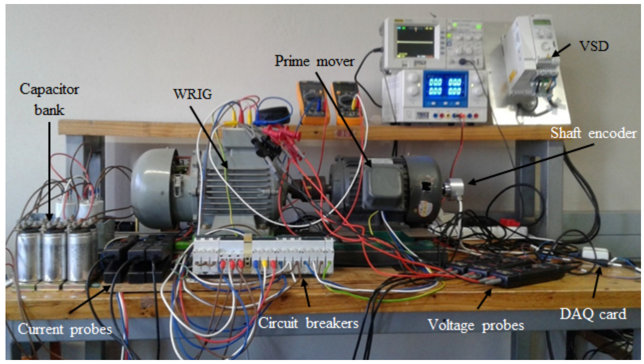

FIGURE 5. Experimental configuration used in investigation.

FIGURE 6. Experimental implementation of stator winding inter-turn short-circuit fault.

The three-phase, 4-pole squirrel cage induction machine, 380V, 50Hz 1.5kW is used a prime mover. The variable speed drive is used to control the speed by adjusting the frequency. The capacitor bank is used to initiate voltage build up and maintain output voltage. It is also used to produce reactive power to supply load requirements as required. An absolute encoder is used to monitor shaft speed and angular position. The data acquisition card enables direct interface to a computer with LabView which is used for the online analysis, testing and validation of condition monitoring system. The voltage differential probes are used for the measurements of induced voltages on the stator winding and the current probes are used for the measurements of stator and rotor winding currents.

The WRIG setup is modified to account for the three fault conditions considered in this research which are inter-turn short circuits on the stator windings and rotor windings, and the brush fault. The inter-turn winding faults for the stator and rotor are implemented on the overhangs of the stator and rotor windings by shorting 3 and 6 adjacent windings as shown in Figures 6 and 7. These faults are implemented by creating a contact between the windings. During this experimental procedure, care was taken to ensure that each fault was implemented and removed such that the short-term effects of fault were minimal to none on the condition of machine - to achieve maximum fault scenario independence. The brush fault is established through an imbalance in the brushes' resistances

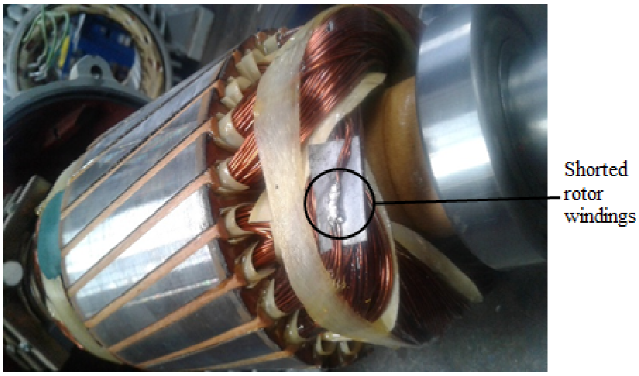

FIGURE 7. Experimental implementation of rotor winding inter-turn short-circuit fault.

and is implemented by connecting a 3.7Ω variable resistor in series with the 'faulty' brush. The experimental WRIG was operated at a speed of 1500 rpm.

The stator voltage, and stator and rotor currents were recorded under no-load and load conditions for each of the healthy and fault scenarios. For each of the generator tests, the procedure is repeated until at least 20 instances/sets of measurements for each scenario is recorded.

D. FAULT CLASSIFICATION

The data acquired through the FE model and experimental measurements were processed and used for training and testing the classifier. The harmonics of each phase voltage and current (11 orders in total from DC component to 10_{th} order or 500 Hz) were extracted and used as features or attributes of the classifier.

The FFT is applied to signals recorded from the cases for healthy, stator- and rotor- winding inter-turn and brush faults. The generated single-sided amplitude spectrum contains the information regarding the different frequency components or harmonics of the signal. The harmonics X_k (magnitude of signal at frequency k) obtained from the FFT are then normalized X_{kN} with respect to the maximum and minimum harmonic, as given by (2). Hence, when normalized, the magnitude of all harmonics orders are calculated with respect to the maximum value, which is the fundamental. This means that the fundamental itself is equal to 1 when normalized. The normalization is done for the following reasons:

- Feature scaling and normalising data for building classifier.
- Provision of better resolution of harmonics which are relatively small compared to the fundamental.
- Fundamental harmonic is treated as only having relative significance. This has the potential benefit of accounting for variations in operating conditions such as shaft speed, although this is not treated within the scope of the presented work.

$$X_{kN} = \frac{X_k - X_{min}}{X_{max} - X_{min}} \tag{2}$$

Each of the first 10 harmonic orders and DC component - i.e. DC component and 50 Hz upto and including 500 Hz of the 3 phases of the generated voltage, and stator and rotor currents were extracted and processed as above. The total features in each modality group consisted of 3 by 10 (11 orders excluding fundamental due to normalization). This yields a total of 90 features in total when the modality groups are combined. These features were extracted from the simulation and experimental data and used to train and test the Naive Bayes, ANN and SVM classifiers in Matlab. Table 3 gives the four different classes corresponding to each of the investigated machine conditions.

TABLE 3. Class assignment of different generator conditions.

Class label	Generator Condition
1	Healthy
2	Brush fault
3	Inter-turn short-circuit fault (stator-winding)
4	Inter-turn short-circuit fault (rotor-winding)

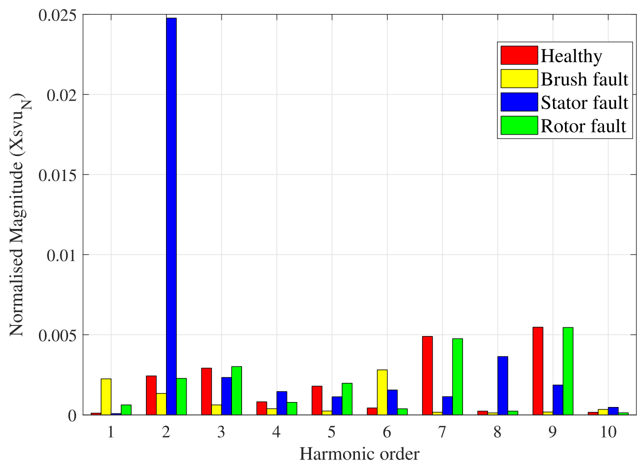

FIGURE 8. Simulated magnitude of phase U stator voltage harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

IV. RESULTS AND ANALYSIS

A. SIMULATION

Figures 8, 9 and 10 show one instance of simulated normalized magnitudes of one phase of each modality - i.e. stator voltage, stator current, and rotor current - for healthy and each of the fault conditions. Multiple variation patterns across different harmonics for each of the cases are observed. Only the first 3 harmonic orders of the rotor current are shown in Figure 10 as the other orders are relatively small to analyse graphically. However, these harmonic orders are incorporated into the classification system as they still provide valuable variation pattern information.

Pattern classification is the act of assigning a class label to an object, physical process or an event, based on some prior information [32]. The behaviours of the phase harmonics of each generator parameter measured display specific patterns corresponding to each fault presented in this investigation.

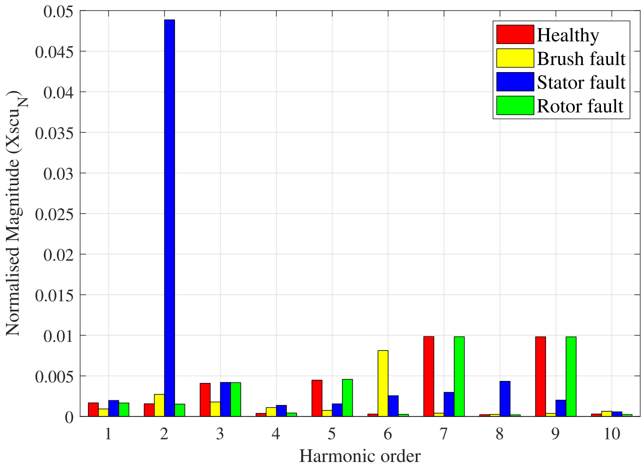

FIGURE 9. Simulated magnitude of phase *U* stator current harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

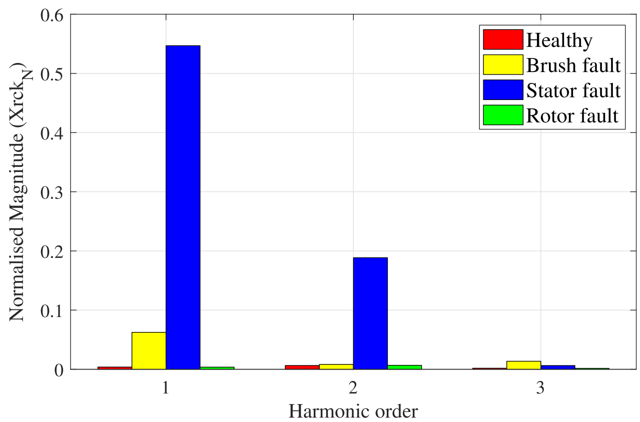

FIGURE 10. Simulated magnitude of phase *K* rotor current harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

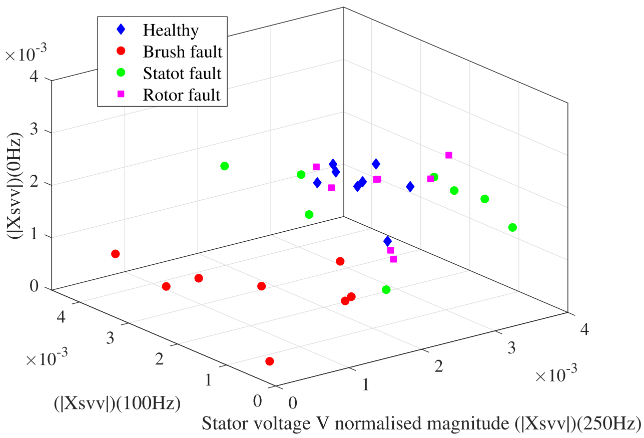

FIGURE 11. Scatter plot of simulated instances indicating ground truth and relationship between feature harmonics (induced stator voltage - phase *V*).

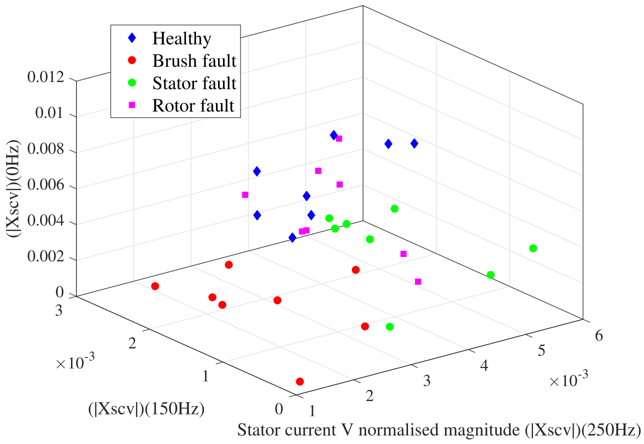

FIGURE 12. Scatter plot of simulated instances indicating ground truth and relationship between feature harmonics (stator current - phase *V*).

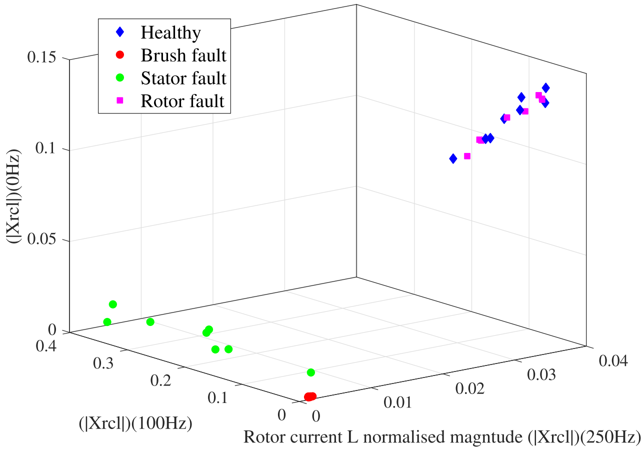

FIGURE 13. Scatter plot of simulated instances indicating ground truth and relationship between feature harmonics (rotor current - phase *L*).

These patterns are more noticeable in the scatter plots shown in Figures 11, 12 and 13 which were generated using the simulated data. The instances used in these scatter plots are shown in terms of only three features grouped according to the different machine conditions. It should be noted that despite analysing this small group of features, a variational trend between each of the machine conditions can be observed. These preliminary simulation results indicated the potential suitability of the selected modalities for classifying the specific fault treated in this work.

B. EXPERIMENTAL

As with the simulation results, the variation patterns observed across the different features were observed in the experimental resulrs. Figures 14, 15 and 16 show one instance of simulated normalized magnitudes of one phase of each modality - i.e. stator voltage, stator current, and rotor current - for healthy and each of the fault conditions. Here also, multiple variation patterns across different harmonics for each of the cases are observed. The first 3 harmonic orders of the rotor current are shown in Figure 16, as similarly with the simulation results, the other orders are relatively small to analyse graphically but are incorporated into the classification system. Some of the experimental results are shown in the form of scatter plots in Figures 17, 18 and 19.

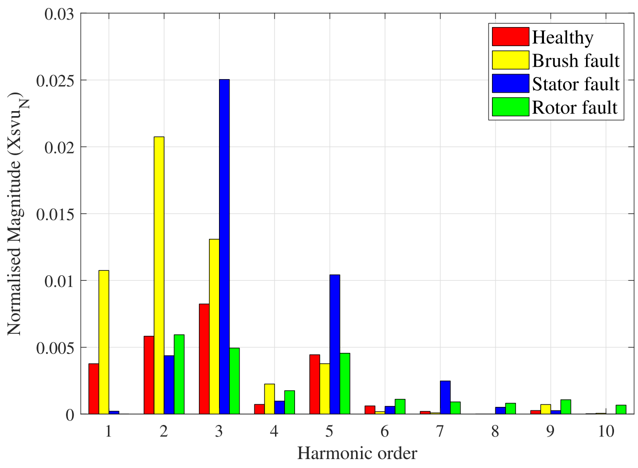

FIGURE 14. Experimental magnitude of phase *U* stator voltage harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

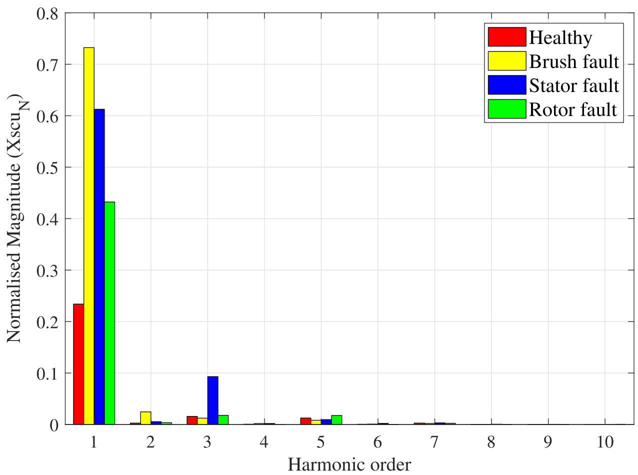

FIGURE 15. Experimental magnitude of phase *U* stator current harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

C. FAULT DIAGNOSIS PERFORMANCE

The variation patterns observed in the simulation results showed a strong case for building and testing of the classification system. The simulated data instances were thus split and 80% were used training and 20% for testing. The summary and diagnostic accuracy of the classification system, based on the simulation data, is given in Table 4. The best overall accuracy achieved for the simulation case was 86% with NBC. As this formed preliminary assessment of the methodology, it was determined that the accuracy of the classification system could be improved and more experimental instances for training and testing were therefore planned and executed. The experimental data instances were split 75% for training and 25% for testing. A summary of the experimental classification system and diagnostic accuracy is also given in Table 4. Overall, it was found that the incorrect fault diagnoses occurred in the form of false negatives in cases of rotor-winding inter-turn short circuit faults - i.e. rotor faults were

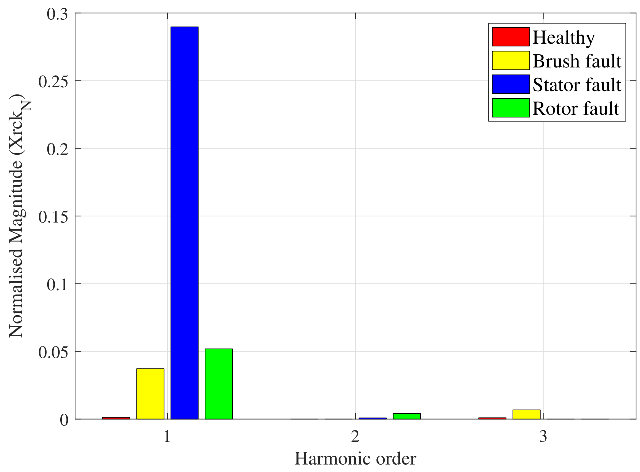

FIGURE 16. Experimental magnitude of phase *K* rotor current harmonic orders (excluding the fundamental due to normalization) for healthy and fault conditions.

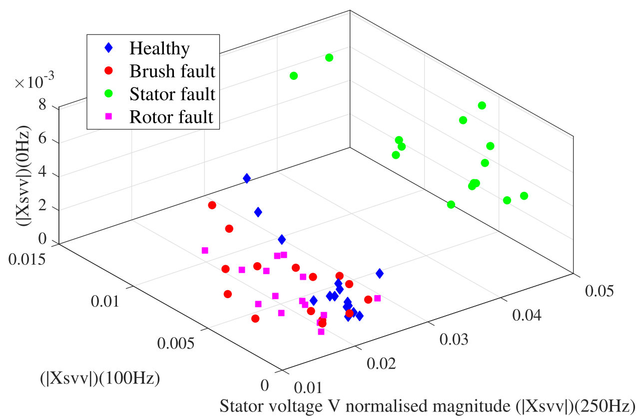

FIGURE 17. Scatter plot of experimental instances indicating ground truth and relationship between feature harmonics (induced stator voltage - phase *V*).

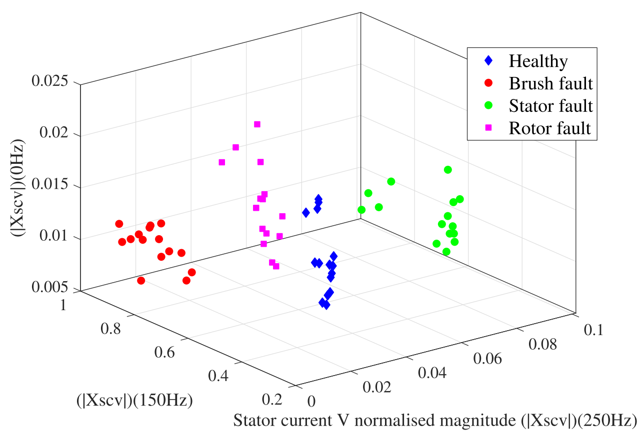

FIGURE 18. Scatter plot of experimental instances indicating ground truth and relationship between feature harmonics (stator current - phase *V*).

present but were incorrectly classified as healthy. It should be noted that ground truth in these cases were 3-turn faults on the rotor winding thereby indicating that the presented methodology may exhibit inaccuracy for lower level rotor

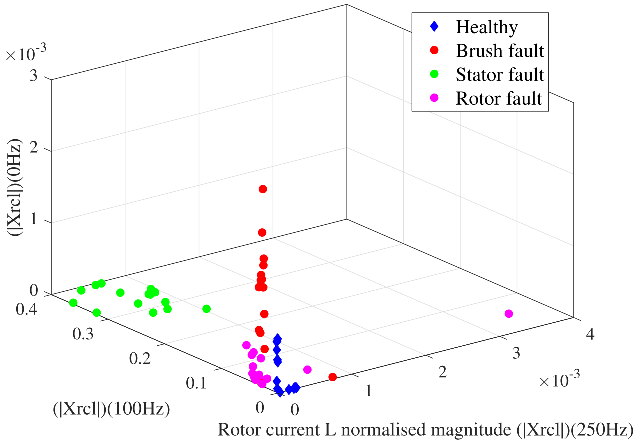

FIGURE 19. Scatter plot of experimental instances indicating ground truth and relationship between feature harmonics (rotor current - phase *L*).

TABLE 4. Summary of classification results.

Parameter	Simulation data	Experimental data
No. of instances	60	120
No. of attributes	90	90
No. of train instances	48	96
No. of test instances	12	24
Accuracy		
NBC	86%	99%
ANN	78%	99%
SVM	68%	50%
Overall error		
NBC	0.09	0.019
ANN	0.12	0.008
SVM	0.16	0.25

winding faults or rotor winding faults at an earlier stage of progression. Comparatively, ANN and NBC achieved the best accuracy for experimental classification.

V. CONCLUSION

This paper presents an investigation of using a combination of electrical signatures or modalities for diagnosis of stator and rotor winding, and brush faults on a WRIG. It is shown that the normalised frequency-based magnitudes of several harmonic orders of the stator voltage and current, and rotor current exhibit patterned variations under the investigated fault conditions. The combined signals' spectra information are used as features to develop a classifier for fault diagnosis. The results of the classifier training and testing, using instances generated from a simulation model and complete experimental setup, is presented. The performance of the measurement modalities, signals processing, and classifier for fault diagnosis yields a best experimental accuracy of 99%. The major findings of the presented work are summarised as follows:

- The WRIG stator voltage and current, and rotor current exhibit differing responses to each of the investigated fault conditions. More specifically, the normalised harmonic orders of the frequency spectra of the various signals show grouped responses corresponding to the ground truths or each of the conditions - i.e. healthy, stator winding fault, rotor winding fault, and brush fault.
- Due to high dimensionality of the response variations, a suitable machine learning technique must be employed to model the variation patterns. The combined use of the spectrum information of the WRIG stator voltage and current, and rotor current as features of a classification system provide good fault resolution and high accuracy fault diagnosis.
- The lower accuracy fault diagnosis for the specific case of the rotor winding 3-turn inter-turn short-circuit fault - i.e. false negative diagnosis - indicates that the presented combination of signals does exhibit some weakness in determining lower-level or earlier-stage rotor winding faults.

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